US012248556B2

(12) **United States Patent**
Demir et al.

(10) **Patent No.: US 12,248,556 B2**
(45) **Date of Patent: Mar. 11, 2025**

(54) **AUTHENTICATOR-INTEGRATED GENERATIVE ADVERSARIAL NETWORK (GAN) FOR SECURE DEEPFAKE GENERATION**

(71) Applicant: **Intel Corporation**, Santa Clara, CA (US)

(72) Inventors: **Ilke Demir**, Hermosa Beach, CA (US); **Carl S. Marshall**, Portland, OR (US); **Satyam Srivastava**, Rancho Cordova, CA (US); **Steven Gans**, San Jose, CA (US)

(73) Assignee: **INTEL CORPORATION**, Santa Clara, CA (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 886 days.

(21) Appl. No.: **17/356,116**

(22) Filed: **Jun. 23, 2021**

(65) **Prior Publication Data**

US 2021/0319090 A1 Oct. 14, 2021

(51) **Int. Cl.**

G06F 21/00	(2013.01)
G06F 21/44	(2013.01)
G06N 3/08	(2023.01)

(52) **U.S. Cl.**
CPC ***G06F 21/44*** (2013.01); ***G06N 3/08*** (2013.01)

(58) **Field of Classification Search**
CPC G06F 21/44; G06N 3/08
See application file for complete search history.

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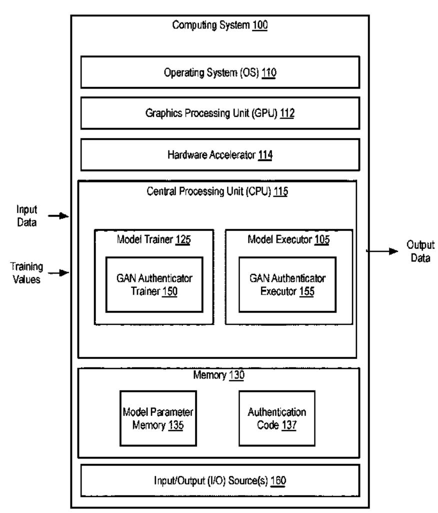
Primary Examiner — Rodman Alexander Mahmoudi
(74) *Attorney, Agent, or Firm* — JAFFREY WATSON MENDONSA & HAMILTON LLP

(57) **ABSTRACT**

An apparatus to facilitate an authenticator-integrated generative adversarial network (GAN) for secure deepfake generation is disclosed. The apparatus includes one or more processors to: generate, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; digest, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network by contributing to a generator loss provided to the generative neural network; generate, by the generative neural network, content comprising the embedded authentication code; and verify, by the authenticator neural network, the content based on the embedded authentication code.

20 Claims, 10 Drawing Sheets



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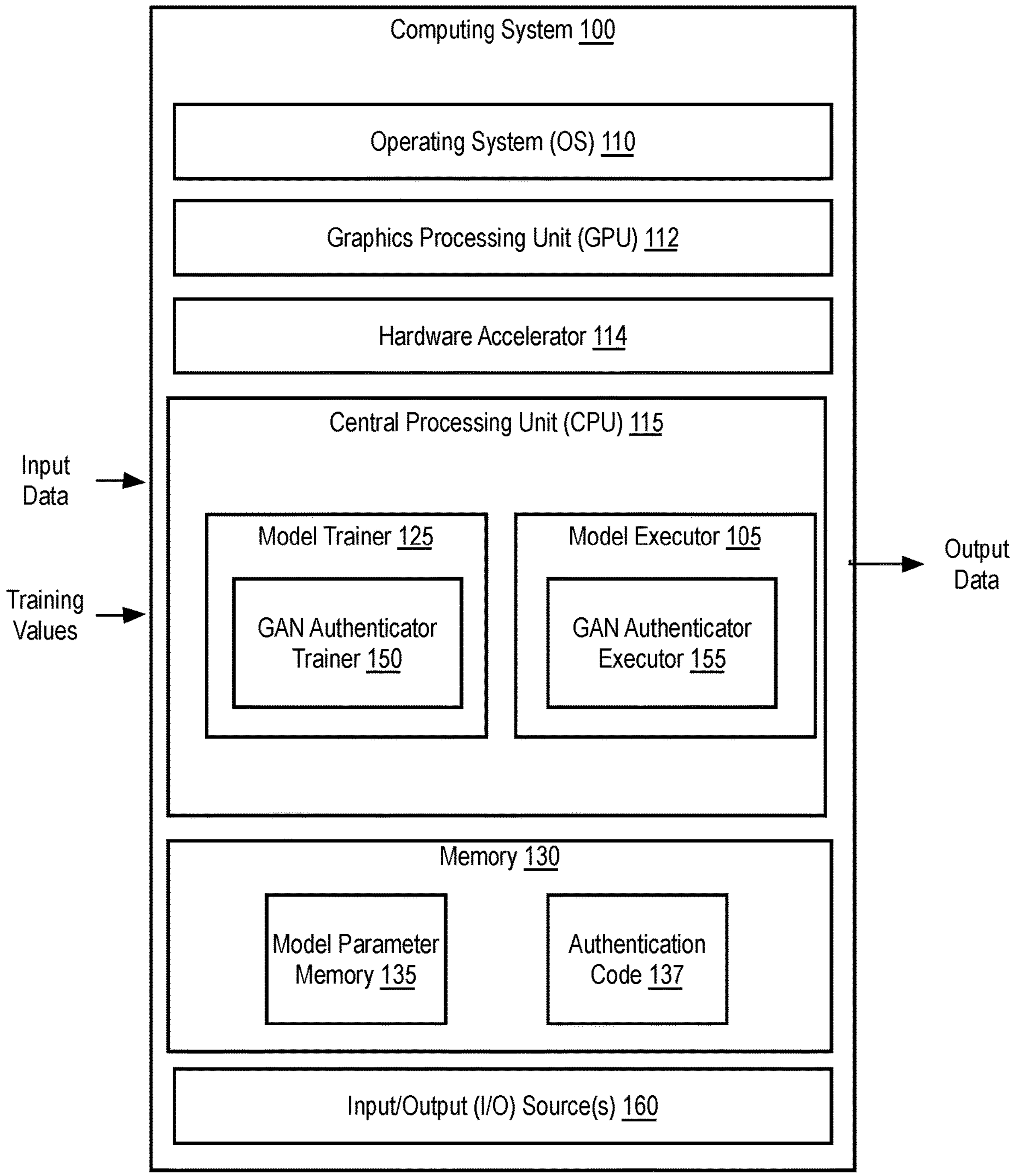
Computing System 100
Operating System (OS) 110
Graphics Processing Unit (GPU) 112
Hardware Accelerator 114
Central Processing Unit (CPU) 115
Input Data
Training Values
Model Trainer 125
GAN Authenticator Trainer 150
Model Executor 105
GAN Authenticator Executor 155
Output Data
Memory 130
Model Parameter Memory 135
Authentication Code 137
Input/Output (I/O) Source(s) 160

FIG. 1

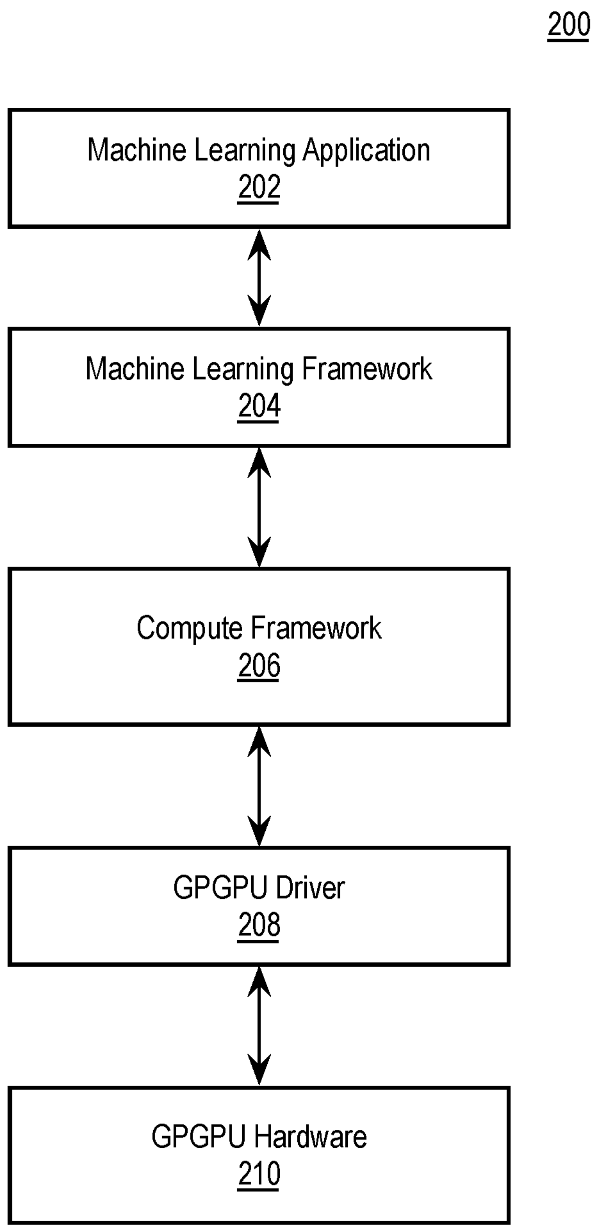
200
Machine Learning Application
202
Machine Learning Framework
204
Compute Framework
206
GPGPU Driver
208
GPGPU Hardware
210

FIG. 2

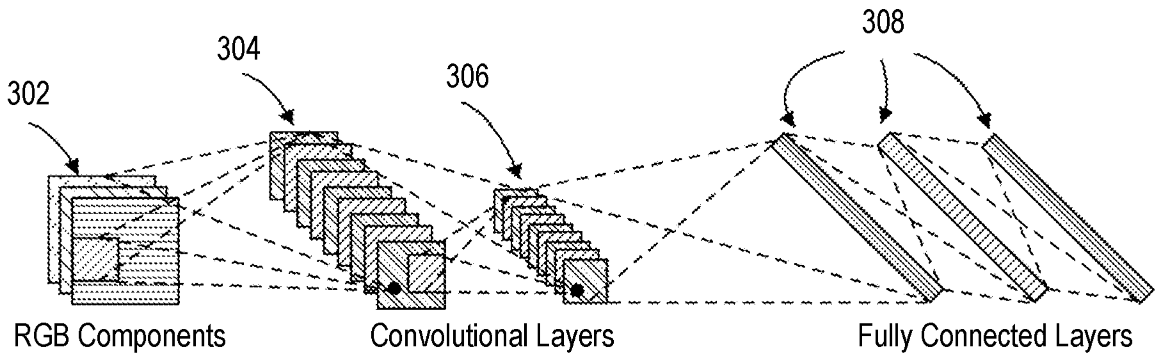
302
304
306
308
RGB Components
Convolutional Layers
Fully Connected Layers

FIG. 3A

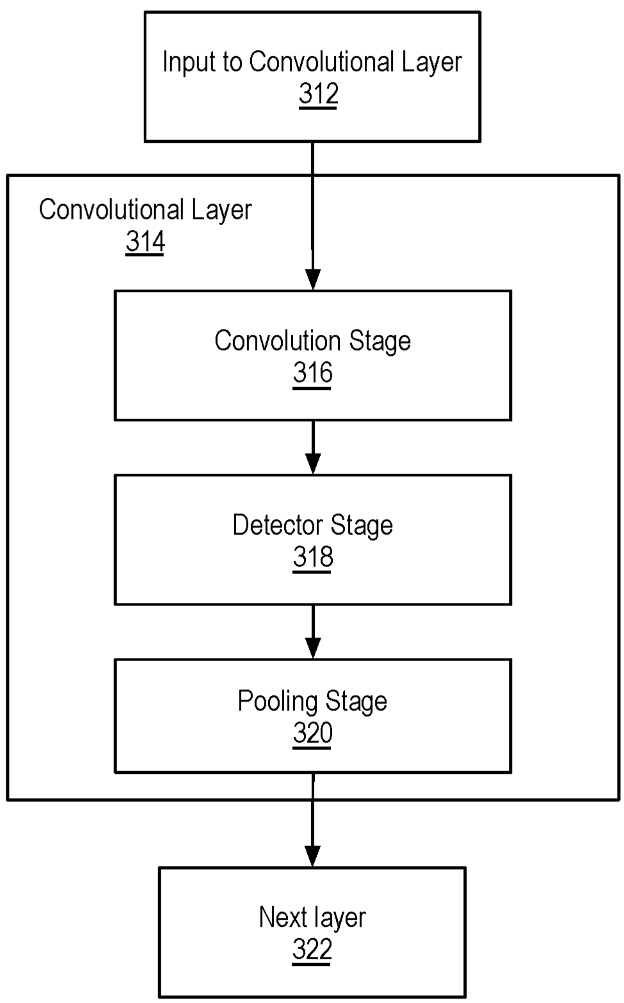
Input to Convolutional Layer
312
Convolutional Layer
314
Convolution Stage
316
Detector Stage
318
Pooling Stage
320
Next layer
322

FIG. 3B

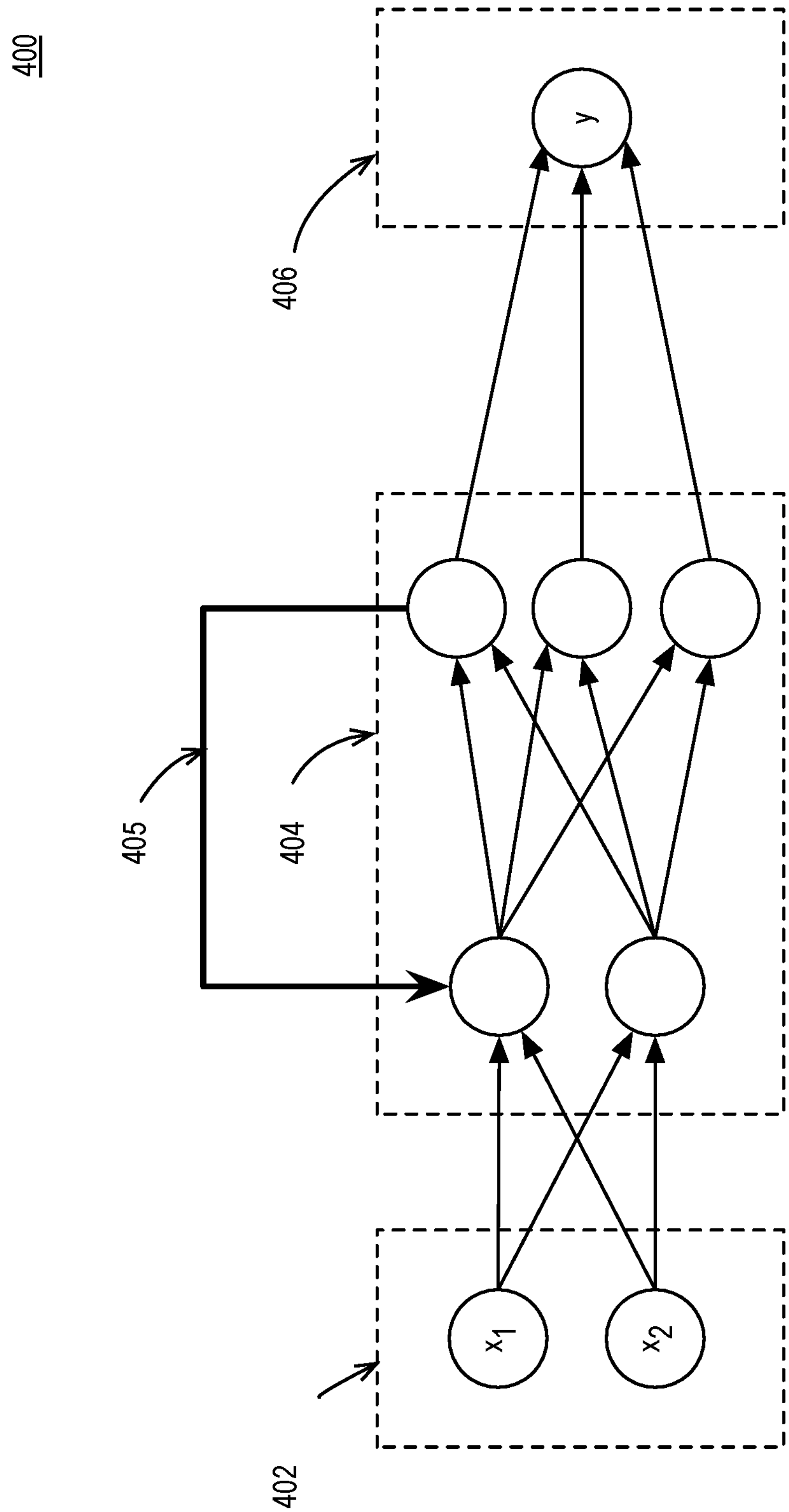

FIG. 4

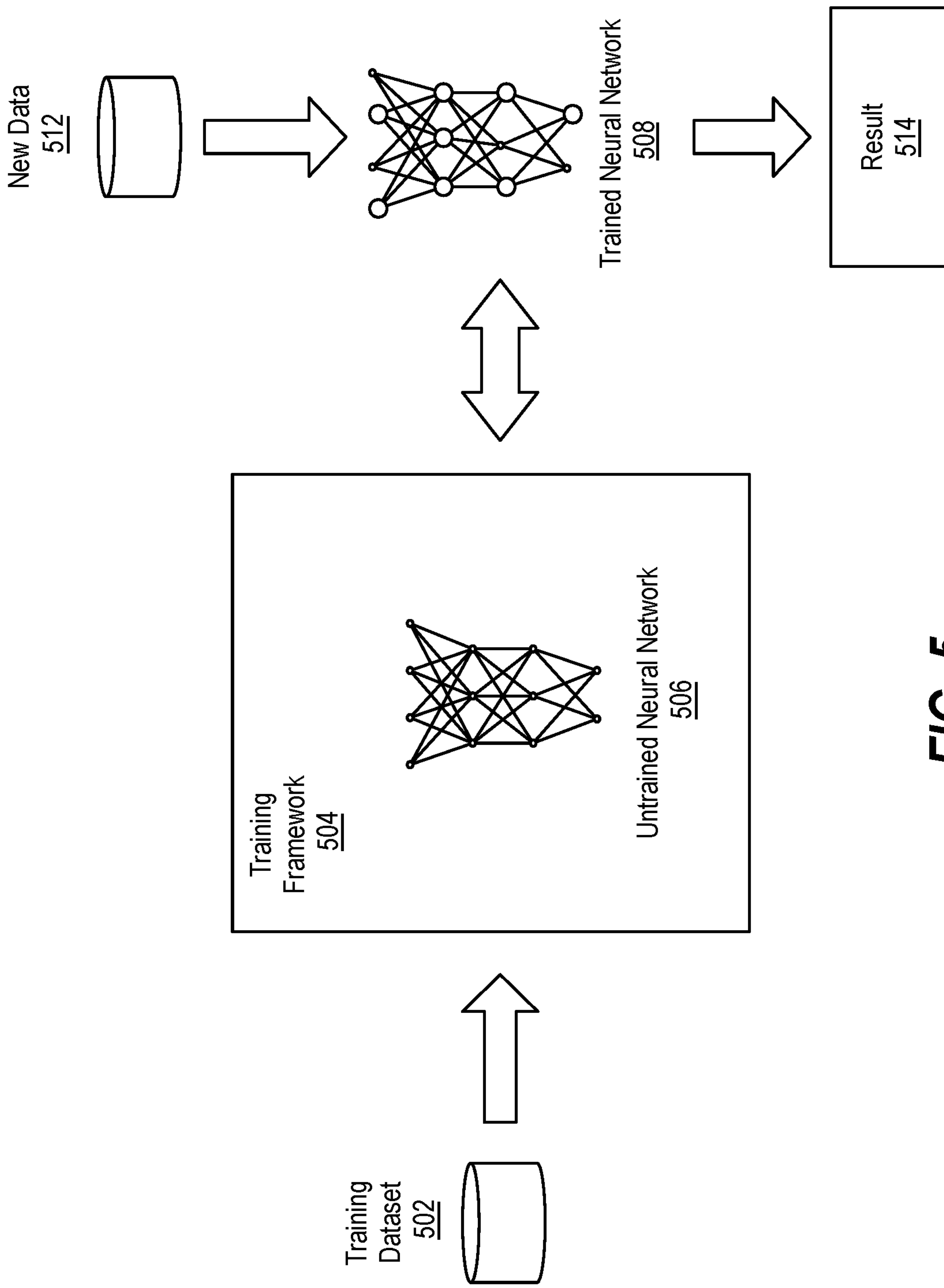
New Data
512
Trained Neural Network
508
Result
514
Training
Framework
504
Untrained Neural Network
506
Training
Dataset
502

FIG. 5

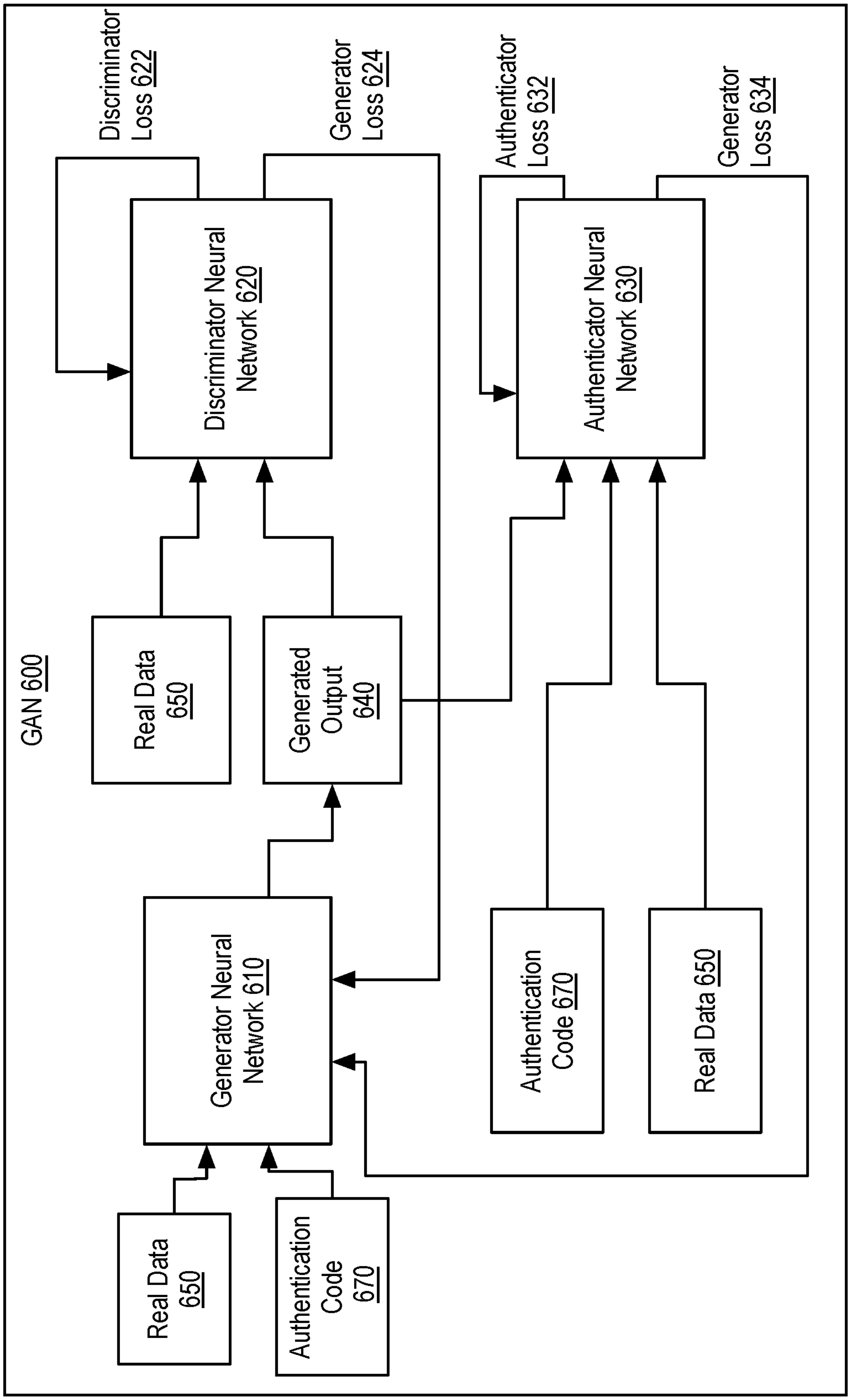
GAN 600
Discriminator Loss 622
Generator Loss 624
Authenticator Loss 632
Generator Loss 634
Discriminator Neural Network 620
Authenticator Neural Network 630
Real Data 650
Generated Output 640
Generator Neural Network 610
Authentication Code 670
Real Data 650
Real Data 650
Authentication Code 670

FIG. 6

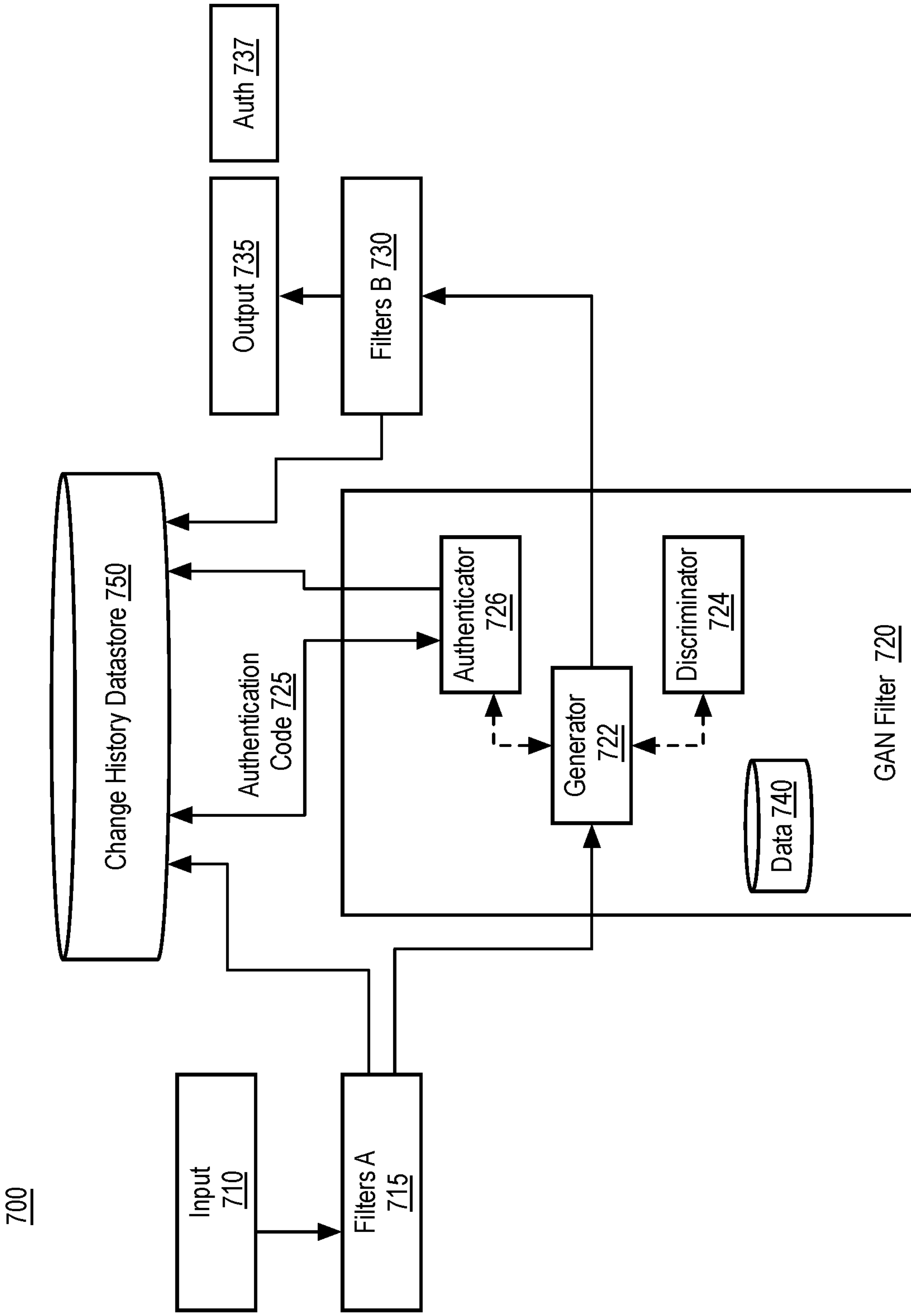
700
Input 710
Filters A 715
Change History Datastore 750
Authentication Code 725
Authenticator 726
Generator 722
Discriminator 724
Data 740
GAN Filter 720
Filters B 730
Output 735
Auth 737

FIG. 7

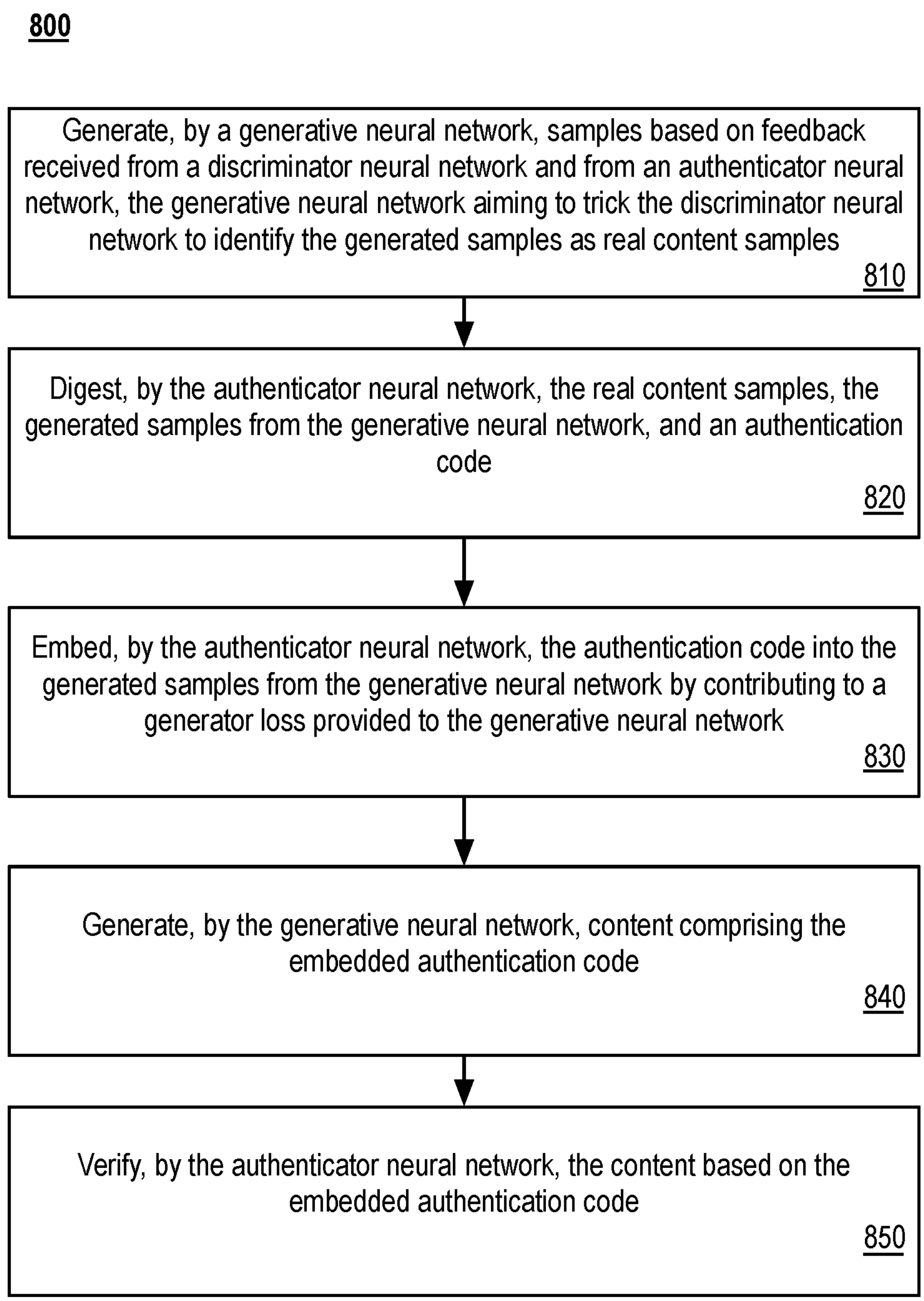
800
Generate, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples
810
Digest, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code
820
Embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network by contributing to a generator loss provided to the generative neural network
830
Generate, by the generative neural network, content comprising the embedded authentication code
840
Verify, by the authenticator neural network, the content based on the embedded authentication code
850

FIG. 8

900

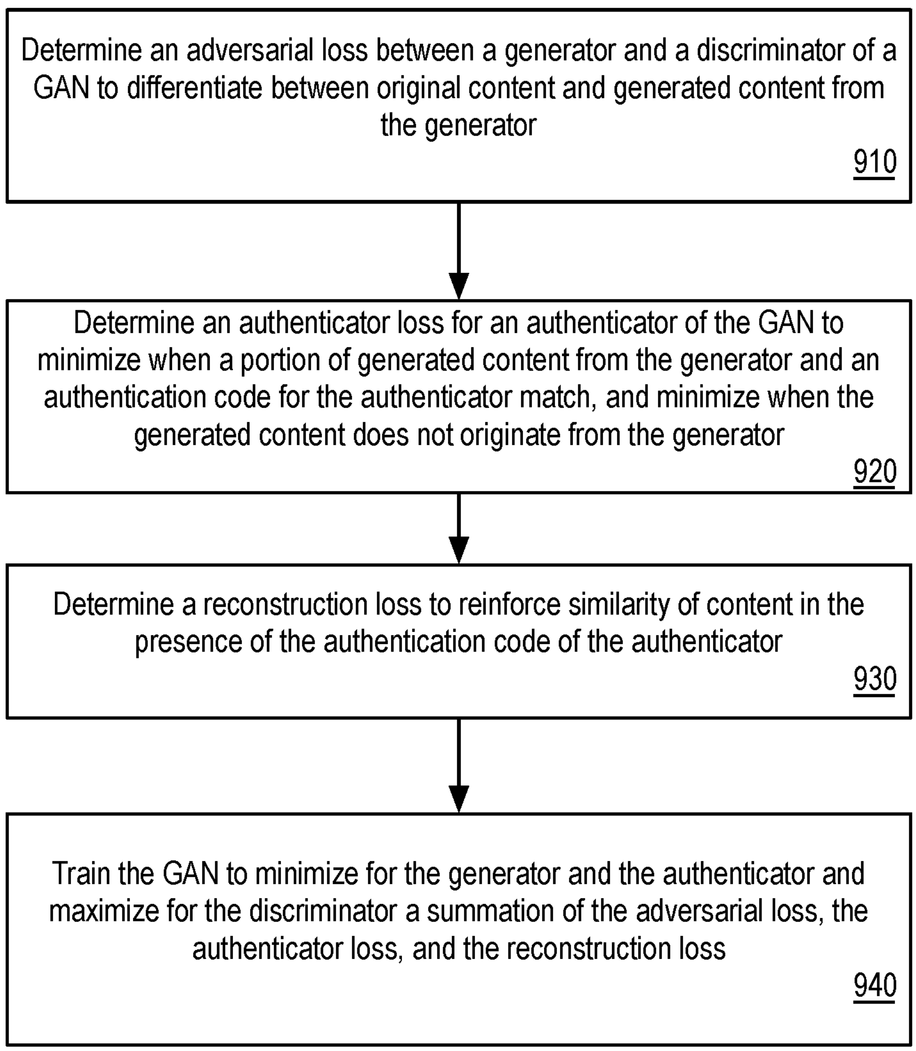
Determine an adversarial loss between a generator and a discriminator of a GAN to differentiate between original content and generated content from the generator
910
Determine an authenticator loss for an authenticator of the GAN to minimize when a portion of generated content from the generator and an authentication code for the authenticator match, and minimize when the generated content does not originate from the generator
920
Determine a reconstruction loss to reinforce similarity of content in the presence of the authentication code of the authenticator
930
Train the GAN to minimize for the generator and the authenticator and maximize for the discriminator a summation of the adversarial loss, the authenticator loss, and the reconstruction loss
940

FIG. 9

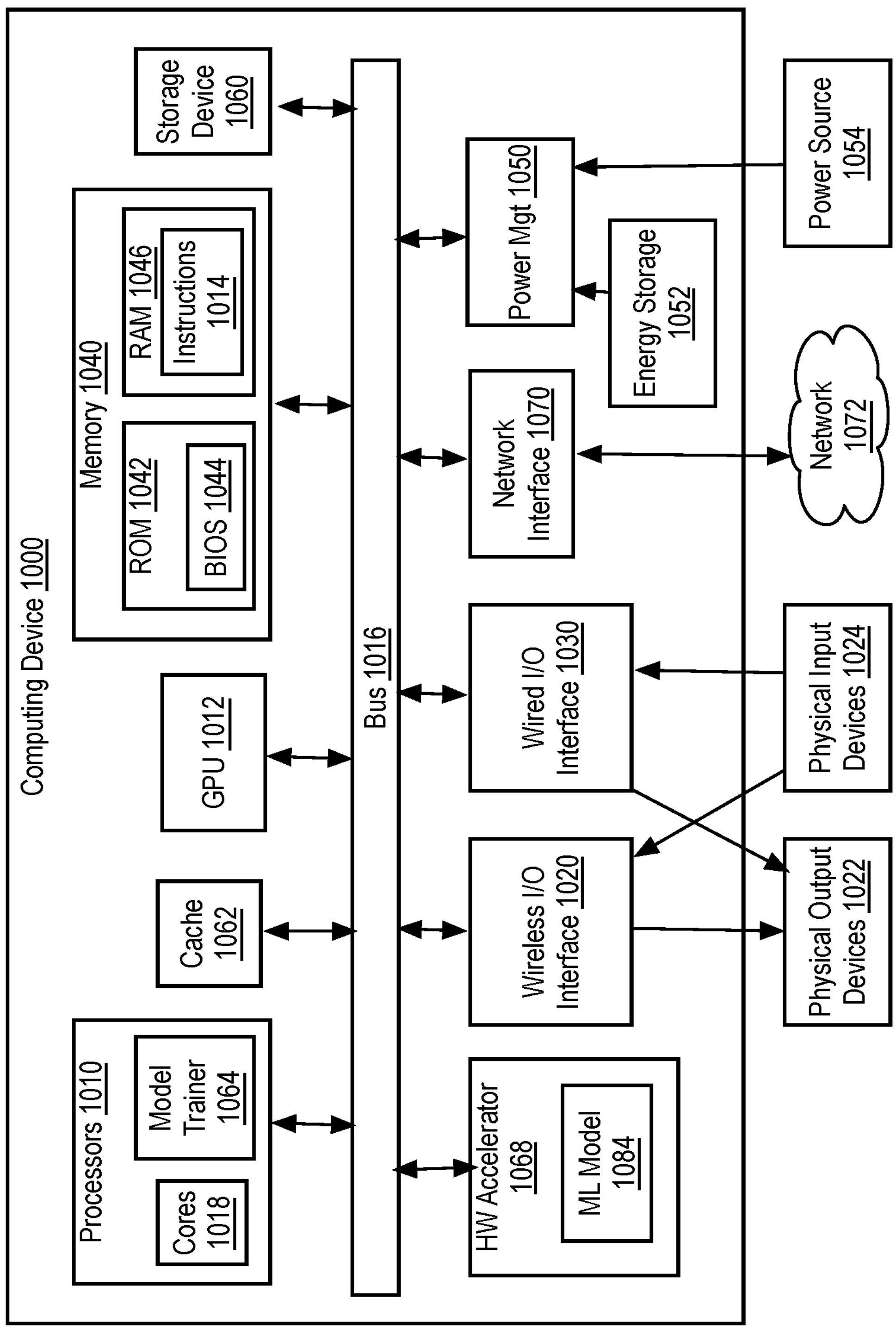
Computing Device 1000
Storage Device 1060
Memory 1040
RAM 1046
Instructions 1014
ROM 1042
BIOS 1044
GPU 1012
Cache 1062
Processors 1010
Model Trainer 1064
Cores 1018
Bus 1016
Power Mgt 1050
Energy Storage 1052
Network Interface 1070
Wired I/O Interface 1030
Wireless I/O Interface 1020
HW Accelerator 1068
ML Model 1084
Power Source 1054
Network 1072
Physical Input Devices 1024
Physical Output Devices 1022

FIG. 10

AUTHENTICATOR-INTEGRATED GENERATIVE ADVERSARIAL NETWORK (GAN) FOR SECURE DEEPFAKE GENERATION

FIELD

Embodiments relate generally to data processing and more particularly to authenticator-integrated generative adversarial network (GAN) for secure deepfake generation.

BACKGROUND OF THE DESCRIPTION

Neural networks and other types of machine learning models are useful tools that have demonstrated their value solving complex problems regarding pattern recognition, natural language processing, automatic speech recognition, etc. Neural networks operate using artificial neurons arranged into one or more layers that process data from an input layer to an output layer, applying weighting values to the data during the processing of the data. Such weighting values are determined during a training process and applied during an inference process.

Neural networks can be leveraged to generate synthetic content in which a person in an existing image or video is replaced with someone else's likeness. Such synthetic content is often referred to as a "deepfake". The main machine learning methods used to create deepfakes are based on deep learning and involve training generative neural network architectures, such as generative adversarial networks (GANs).

With the advent of deepfakes, the development of deepfake detection techniques has also proliferated. In the current state of the art, deepfake detection techniques may operate specifically per source generators, per impersonated persons, or per specific features.

BRIEF DESCRIPTION OF THE DRAWINGS

So that the manner in which the above recited features of the present embodiments can be understood in detail, a more particular description of the embodiments, briefly summarized above, may be had by reference to embodiments, some of which are illustrated in the appended drawings. It is to be noted, however, that the appended drawings illustrate typical embodiments and are therefore not to be considered limiting of its scope. The figures are not to scale. In general, the same reference numbers are used throughout the drawing(s) and accompanying written description to refer to the same or like parts.

FIG. **1** is a block diagram of an example computing system that may be used to provide an authenticator-integration generative adversarial network (GAN) for secure deepfake generation, according to implementations of the disclosure.

FIG. **2** illustrates a machine learning software stack, according to an embodiment.

FIGS. **3**A-**3**B illustrate layers of example deep neural networks.

FIG. **4** illustrates an example recurrent neural network.

FIG. **5** illustrates training and deployment of a deep neural network.

FIG. **6** depicts a GAN system providing an authenticator-integrated GAN for secure deepfake generation, in accordance with implementations of the disclosure.

FIG. **7** depicts a schematic of an illustrative flow of an authenticator-integrated GAN system providing secure deepfake detection, in accordance with implementations of the disclosure.

FIG. **8** is a flow diagram illustrating an embodiment of a method for a secure deepfake generation using an authenticator-integrated GAN.

FIG. **9** is a flow diagram illustrating an embodiment of a method **900** for training an authenticator-integrated GAN for secure deepfake generation.

FIG. **10** is a schematic diagram of an illustrative electronic computing device to enable an authenticator-integration GAN for secure deepfake generation, according to some implementations.

DETAILED DESCRIPTION

Implementations of the disclosure describe an authenticator-integrated generative adversarial network (GAN) for secure deepfake generation. In computer engineering, computing architecture is a set of rules and methods that describe the functionality, organization, and implementation of computer systems. Today's computing systems are expected to deliver near zero-wait responsiveness and superb performance while taking on large workloads for execution. Therefore, computing architectures have continually changed (e.g., improved) to accommodate demanding workloads and increased performance expectations.

Examples of large workloads include neural networks, artificial intelligence (AI), machine learning, etc. Such workloads have become more prevalent as they have been implemented in a number of computing devices, such as personal computing devices, business-related computing devices, etc. Furthermore, with the growing use of large machine learning and neural network workloads, new silicon has been produced that is targeted at running large workloads. Such new silicon includes dedicated hardware accelerators (e.g., graphics processing unit (GPU), field-programmable gate array (FPGA), vision processing unit (VPU), etc.) customized for processing data using data parallelism.

Artificial intelligence (AI), including machine learning (ML), deep learning (DL), neural networks, and/or other artificial machine-driven logic, enables machines (e.g., computers, logic circuits, etc.) to use a model to process input data to generate an output based on patterns and/or associations previously learned by the model via a training process. For instance, the model may be trained with data to recognize patterns and/or associations and follow such patterns and/or associations when processing input data such that other input(s) result in output(s) consistent with the recognized patterns and/or associations.

Many different types of machine learning models and/or machine learning architectures exist. In some examples disclosed herein, a convolutional neural network is used. Using a convolutional neural network (CNN) enables classification of objects in images, natural language processing, etc. In general, machine learning models/architectures that are suitable to use in the example approaches disclosed herein may include convolutional neural networks. However, other types of machine learning models could additionally or alternatively be used such as recurrent neural network, feedforward neural network, generative adversarial network (GAN), etc.

In general, implementing a ML/AI system involves two phases, a learning/training phase and an inference phase. In the learning/training phase, a training algorithm is used to train a model to operate in accordance with patterns and/or associations based on, for example, training data. In general, the model includes internal parameters that guide how input data is transformed into output data, such as through a series of nodes and connections within the model to transform input data into output data. Additionally, hyperparameters are used as part of the training process to control how the learning is performed (e.g., a learning rate, a number of layers to be used in the machine learning model, etc.). Hyperparameters are defined to be training parameters that are determined prior to initiating the training process.

Different types of training may be performed based on the type of ML/AI model and/or the expected output. For example, supervised training uses inputs and corresponding expected (e.g., labeled) outputs to select parameters (e.g., by iterating over combinations of select parameters) for the ML/AI model that reduce model error. As used herein, labelling refers to an expected output of the machine learning model (e.g., a classification, an expected output value, etc.) Alternatively, unsupervised training (e.g., used in deep learning, a subset of machine learning, etc.) involves inferring patterns from inputs to select parameters for the ML/AI model (e.g., without the benefit of expected (e.g., labeled) outputs).

Neural networks can be leveraged to generate synthetic content in which a person in an existing image or video is replaced with someone else's likeness. Such synthetic content is often referred to as a "deepfake". The main machine learning methods used to create deepfakes are based on deep learning and involve training generative neural network architectures, such as GANs. GANs are a class of ML frameworks where two neural networks (e.g., a "generative network" (or generator) and a "discriminative network" (or discriminator)) contest with each other in a game (in the form of a zero-sum game, where one agent's gain is another agent's loss). Given a training set, the GAN learns to generate new data with the same statistics as the training set. For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics. The core idea of a GAN is based on the "indirect" training through a discriminator, which itself is also being updated dynamically. This means that the generator is not trained to minimize the distance to a specific image, but rather to fool the discriminator. This enables the GAN to learn in an "unsupervised" manner.

As deep fakes become more popular, their use with malicious intent is endangering the public trust mechanisms. On the other hand, generative modeling has been used for positive purposes in media, entertainment, and augmented reality (AR)/virtual reality (VR) domains for decades. The proliferation of deepfakes can obscure the creative and authentic uses of generative models. Traditional authentication approaches (such as watermarking) become obsolete in this new context due to the complex generation process. Thus, implementations of the disclosure provide for authentication as a part of the generation process of GANs by creating trackable content.

Conventional methods for deepfake detection rely on training a classifier on a large collection of datasets to determine the common attributes that statistically work "well" for a group of subjects for deepfake detection. However, a drawback to the conventional approaches for deepfake detection is that they did not allow for marking mark content as originating from a particular generator. Conventional methods do not provide for this type of authentication of origin verification for GAN-generated content and/or GAN-based approaches.

Implementations of the disclosure address these drawbacks by providing an authenticator-integrated GAN architecture for deepfake origin verification. As noted above, GANs consist of a generator and a discriminator structure where the generator attempts to trick the discriminator to believe the generated content is real (e.g., real content samples), and the discriminator attempts to classify the real and generated content correctly. Implementations of the disclosure augment the conventional GAN architecture with a third component: the authenticator. In implementations of the disclosure, the authenticator can digest real and fake data, similar to a discriminator, and also can digest a private code (also referred to herein as an authentication code). The authenticator seeks to embed the private code (as an embedded authentication code) into the generated samples by contributing to the generator loss, and seeks to learn an internal embedding of the private code related to the distribution of the generated samples from the generator. The generator helps the authenticator, in contrast to tricking the discriminator. As a result, implementations of the disclosure provide an approach to authenticate the GAN-generated content as originating from a GAN generator.

Implementations of the disclosure provide for a variety of technical advantages over the conventional approaches. Advantages of implementations of the disclosure include improved deepfake detection accuracy, improved content moderation, improved detection of harmful video marking, and/or enable limiting illegal uses of deepfakes. Implementations of the disclosure also provide an improved approach to verify the origination of and/or authenticity of GAN-based content, which can be used in one or more of verification of original content, creative content authentication, and/or provenance for legal uses of generative models.

FIG. **1** is a block diagram of an example computing system that may be used to implement an authenticator-integrated GAN for secure deepfake generation, according to implementations of the disclosure. The example computing system **100** may be implemented as a component of another system such as, for example, a mobile device, a wearable device, a laptop computer, a tablet, a desktop computer, a server, etc. In one embodiment, computing system **100** includes or can be integrated within (without limitation): a server-based gaming platform; a game console, including a game and media console; a mobile gaming console, a handheld game console, or an online game console. In some embodiments the computing system **100** is part of a mobile phone, smart phone, tablet computing device or mobile Internet-connected device such as a laptop with low internal storage capacity.

In some embodiments the computing system **100** is part of an Internet-of-Things (IoT) device, which are typically resource-constrained devices. IoT devices may include embedded systems, wireless sensor networks, control systems, automation (including home and building automation), and other devices and appliances (such as lighting fixtures, thermostats, home security systems and cameras, and other home appliances) that support one or more common ecosystems, and can be controlled via devices associated with that ecosystem, such as smartphones and smart speakers.

Computing system **100** can also include, couple with, or be integrated within: a wearable device, such as a smart watch wearable device; smart eyewear or clothing enhanced with augmented reality (AR) or virtual reality (VR) features to provide visual, audio or tactile outputs to supplement real world visual, audio or tactile experiences or otherwise provide text, audio, graphics, video, holographic images or video, or tactile feedback; other augmented reality (AR) device; or other virtual reality (VR) device. In some embodiments, the computing system **100** includes or is part of a television or set top box device. In one embodiment, computing system **100** can include, couple with, or be integrated within a self-driving vehicle such as a bus, tractor trailer, car, motor or electric power cycle, plane or glider (or any combination thereof). The self-driving vehicle may use computing system **100** to process the environment sensed around the vehicle.

As illustrated, in one embodiment, computing system **100** may include any number and type of hardware and/or software components, such as (without limitation) graphics processing unit ("GPU", general purpose GPU (GPGPU), or simply "graphics processor") **112**, a hardware accelerator **114**, central processing unit ("CPU" or simply "application processor") **115**, memory **130**, network devices, drivers, or the like, as well as input/output (I/O) sources **160**, such as touchscreens, touch panels, touch pads, virtual or regular keyboards, virtual or regular mice, ports, connectors, etc. Computing system **100** may include operating system (OS) **110** serving as an interface between hardware and/or physical resources of the computing system **100** and a user. In some implementations, the computing system **100** may include a combination of one or more of the CPU **115**, GPU **112**, and/or hardware accelerator **114** on a single system on a chip (SoC), or may be without a GPU **112** or visual output (e.g., hardware accelerator **114**) in some cases, etc.

As used herein, "hardware accelerator", such as hardware accelerator **114**, refers to a hardware device structured to provide for efficient processing. In particular, a hardware accelerator may be utilized to provide for offloading of some processing tasks from a central processing unit (CPU) or other general processor, wherein the hardware accelerator may be intended to provide more efficient processing of the processing tasks than software run on the CPU or other processor. A hardware accelerator may include, but is not limited to, a graphics processing unit (GPU), a vision processing unit (VPU), neural processing unit, AI (Artificial Intelligence) processor, field programmable gate array (FPGA), or application-specific integrated circuit (ASIC).

The GPU **112** (or graphics processor **112**), hardware accelerator **114**, and/or CPU **115** (or application processor **115**) of example computing system **100** may include a model trainer **125** and model executor **105**. Although the model trainer **125** and model executor **105** are depicted as part of the CPU **115**, in some implementations, the GPU **112** and/or hardware accelerator **114** may include the model trainer **125** and model executor **105**.

The example model executor **105** accesses input values (e.g., via an input interface (not shown)), and processes those input values based on a machine learning model stored in a model parameter memory **135** of the memory **130** to produce output values (e.g., via an output interface (not shown)). The input data may be received from one or more data sources (e.g., via one or more sensors, via a network interface, etc.). However, the input data may be received in any fashion such as, for example, from an external device (e.g., via a wired and/or wireless communication channel). In some examples, multiple different types of inputs may be received. In some examples, the input data and/or output data is received via inputs and/or outputs of the system of which the computing system **100** is a component.

In the illustrated example of FIG. **1**, the example neural network parameters stored in the model parameter memory **135** are trained by the model trainer **125** such that input training data (e.g., received via a training value interface (not shown)) results in output values based on the training data. In the illustrated example of FIG. **1**, the model trainer **125** can include an embedded GAN authenticator trainer **150** that is utilized when processing the model during training and/or inference. In implementations of the disclosure, a trained GAN authenticator generated by the GAN authenticator trainer **150** is provided to a GAN authenticator executor **155** embedded in model executor **105** to execute a trained GAN authenticator as part of a GAN for secure deepfake detection, authentication, and/or verification using an authentication code **137** (e.g., stored in memory **130**).

The example model executor **105**, the example model trainer **125**, the example GAN authenticator trainer **150**, and/or the example GAN authenticator executor **155** are implemented by one or more logic circuits such as, for example, hardware processors. In some examples, one or more of the example model executor **105**, the example model trainer **125**, the example GAN authenticator trainer **150**, and/or the example GAN authenticator executor **155** may be implemented by a same hardware component (e.g., a same logic circuit) or by different hardware components (e.g., different logic circuits, different computing systems, etc.). However, any other type of circuitry may additionally or alternatively be used such as, for example, one or more analog or digital circuit(s), logic circuits, programmable processor(s), application specific integrated circuit(s) (ASIC(s)), programmable logic device(s) (PLD(s)), field programmable logic device(s) (FPLD(s)), digital signal processor(s) (DSP(s)), etc.

In examples disclosed herein, the example model executor **105** executes a machine learning model. The example machine learning model may be implemented using a neural network (e.g., a feedforward neural network). However, any other past, present, and/or future machine learning topology(ies) and/or architecture(s) may additionally or alternatively be used such as, for example, a CNN.

To execute a model, the example model executor **105** accesses input data. The example model executor **105** applies the model (defined by the model parameters (e.g., neural network parameters including weight and/or activations) stored in the model parameter memory **135**) to the input data.

The example model parameter memory **135** of the illustrated example of FIG. **1** is implemented by any memory, storage device and/or storage disc for storing data such as, for example, flash memory, magnetic media, optical media, etc. Furthermore, the data stored in the example model parameter memory **135** may be in any data format such as, for example, binary data, comma delimited data, tab delimited data, structured query language (SQL) structures, etc. While in the illustrated example the model parameter memory **135** is illustrated as a single element, the model parameter memory **135** and/or any other data storage elements described herein may be implemented by any number and/or type(s) of memories. In the illustrated example of FIG. **1**, the example model parameter memory **135** stores model weighting parameters that are used by the model executor **105** to process inputs for generation of one or more outputs as output data.

In examples disclosed herein, the output data may be information that classifies the received input data (e.g., as determined by the model executor **105**.). However, any other type of output that may be used for any other purpose may additionally or alternatively be used. In examples disclosed herein, the output data may be output by an input/output

(I/O) source **160** that displays the output values. However, in some examples, the output data may be provided as output values to another system (e.g., another circuit, an external system, a program executed by the computing system **100**, etc.). In some examples, the output data may be stored in a memory.

The example model trainer **125** of the illustrated example of FIG. **1** compares expected outputs (e.g., received as training values at the computing system **100**) to outputs produced by the example model executor **105** to determine an amount of training error, and updates the model parameters (e.g., model parameter memory **135**) based on the amount of error. After a training iteration, the amount of error is evaluated by the model trainer **125** to determine whether to continue training. In examples disclosed herein, errors are identified when the input data does not result in an expected output. That is, error is represented as a number of incorrect outputs given inputs with expected outputs. However, any other approach to representing error may additionally or alternatively be used such as, for example, a percentage of input data points that resulted in an error.

The example model trainer **125** determines whether the training error is less than a training error threshold. If the training error is less than the training error threshold, then the model has been trained such that it results in a sufficiently low amount of error, and no further training is pursued. In examples disclosed herein, the training error threshold is ten errors. However, any other threshold may additionally or alternatively be used. Moreover, other types of factors may be considered when determining whether model training is complete. For example, an amount of training iterations performed and/or an amount of time elapsed during the training process may be considered.

The training data that is utilized by the model trainer **125** includes example inputs (corresponding to the input data expected to be received), as well as expected output data. In examples disclosed herein, the example training data is provided to the model trainer **125** to enable the model trainer **125** to determine an amount of training error.

In examples disclosed herein, the example model trainer **125** utilizes the combination of the example GAN authenticator trainer **150** and the example GAN authenticator executor **155** to implement secure deepfake detection using an authenticator-integrated GAN. In implementations of the disclosure, the authenticator-integrated GAN for secure deepfake detection can include an authenticator neural network of the GAN embedding an authentication code, such as authentication code **137**, in synthesized content generated by a generator of the GAN. In one implementation, the GAN authenticator trainer **150** of the example model trainer **125** used in combination with the GAN authenticator executor described with respect to FIG. **1** provides for the secure deepfake detection using an authenticator-integrated GAN, as described herein.

As discussed above, to train a model, such as a machine learning model utilizing a neural network, such as a GAN, the example model trainer **125** trains a machine learning model using the GAN authenticator trainer **150**. As noted above, GANs consist of a generator and a discriminator structure where the generator attempts to trick the discriminator to believe the generated content is real, and the discriminator attempts to classify the real and generated content correctly. Implementations of the disclosure augment the conventional GAN architecture with a third component: the authenticator, that is trained and executed by GAN authenticator trainer **150** and GAN authenticator executor **155**, respectively.

In implementations of the disclosure, the authenticator can digest real and fake data, similar to a discriminator, and also can digest a private code (also referred to herein as an authentication code). The authenticator seeks to embed the private code into the generated samples by contributing to the generator loss, and seeks to learn an internal embedding of the private code related to the distribution of the generated samples from the generator. The generator helps the authenticator, in contrast to tricking the discriminator. As a result, implementations of the disclosure provide an approach to authenticate the GAN-generated content as originating from a GAN generator. Further discussion and detailed description of the model trainer **125**, the mode executor **105**, the GAN authenticator trainer **150**, and the GAN authenticator executor **155** are provided below with respect to FIGS. **2-10**.

The example I/O source **160** of the illustrated example of FIG. **1** enables communication of the model stored in the model parameter memory **135** with other computing systems. In some implementations, the I/O source(s) **160** may include, at but is not limited to, a network device, a microprocessor, a camera, a robotic eye, a speaker, a sensor, a display screen, a media player, a mouse, a touch-sensitive device, and so on. In this manner, a central computing system (e.g., a server computer system) can perform training of the model and distribute the model to edge devices for utilization (e.g., for performing inference operations using the model). In examples disclosed herein, the I/O source **160** is implemented using an Ethernet network communicator. However, any other past, present, and/or future type(s) of communication technologies may additionally or alternatively be used to communicate a model to a separate computing system.

While an example manner of implementing the computing system **100** is illustrated in FIG. **1**, one or more of the elements, processes and/or devices illustrated in FIG. **1** may be combined, divided, re-arranged, omitted, eliminated and/or implemented in any other way. Further, the example model executor **105**, the example model trainer **125**, the example GAN authenticator trainer **150**, the example GAN authenticator executor **155**, the I/O source(s) **160**, and/or, more generally, the example computing system **100** of FIG. **1** may be implemented by hardware, software, firmware and/or any combination of hardware, software and/or firmware. Thus, for example, any of the example model executor **105**, the example model trainer **125**, the example GAN authenticator trainer **150**, the example GAN authenticator executor **155**, the example I/O source(s) **160**, and/or, more generally, the example computing system **100** of FIG. **1** could be implemented by one or more analog or digital circuit(s), logic circuits, programmable processor(s), programmable controller(s), graphics processing unit(s) (GPU(s)), digital signal processor(s) (DSP(s)), application specific integrated circuit(s) (ASIC(s)), programmable logic device(s) (PLD(s)) and/or field programmable logic device(s) (FPLD(s)).

In some implementations of the disclosure, a software and/or firmware implementation of at least one of the example model executor **105**, the example model trainer **125**, the example GAN authenticator trainer **150**, the example GAN authenticator executor **155**, the example I/O source(s) **160**, and/or, more generally, the example computing system **100** of FIG. **1** be provided. Such implementations can include a non-transitory computer readable storage device or storage disk (also referred to herein as a non-transitory computer-readable storage medium) such as a memory, a digital versatile disk (DVD), a compact disk (CD), a Blu-ray disk, etc. including the software and/or firmware. Further still, the example computing system **100** of FIG. **1** may include one or more elements, processes and/or devices in addition to, or instead of, those illustrated in FIG. **1**, and/or may include more than one of any or all of the illustrated elements, processes, and devices. As used herein, the phrase "in communication," including variations thereof, encompasses direct communication and/or indirect communication through one or more intermediary components, and does not utilize direct physical (e.g., wired) communication and/or constant communication, but rather additionally includes selective communication at periodic intervals, scheduled intervals, aperiodic intervals, and/or one-time events.

Machine Learning Overview

A machine learning algorithm is an algorithm that can learn based on a set of data. Embodiments of machine learning algorithms can be designed to model high-level abstractions within a data set. For example, image recognition algorithms can be used to determine which of several categories to which a given input belong; regression algorithms can output a numerical value given an input; and pattern recognition algorithms can be used to generate translated text or perform text to speech and/or speech recognition.

An example type of machine learning algorithm is a neural network. There are many types of neural networks; a simple type of neural network is a feedforward network. A feedforward network may be implemented as an acyclic graph in which the nodes are arranged in layers. Typically, a feedforward network topology includes an input layer and an output layer that are separated by at least one hidden layer. The hidden layer transforms input received by the input layer into a representation that is useful for generating output in the output layer. The network nodes are fully connected via edges to the nodes in adjacent layers, but there are no edges between nodes within each layer. Data received at the nodes of an input layer of a feedforward network are propagated (i.e., "fed forward") to the nodes of the output layer via an activation function that calculates the states of the nodes of each successive layer in the network based on coefficients ("weights") respectively associated with each of the edges connecting the layers. Depending on the specific model being represented by the algorithm being executed, the output from the neural network algorithm can take various forms.

Before a machine learning algorithm can be used to model a particular problem, the algorithm is trained using a training data set. Training a neural network involves selecting a network topology, using a set of training data representing a problem being modeled by the network, and adjusting the weights until the network model performs with a minimal error for all instances of the training data set. For example, during a supervised learning training process for a neural network, the output produced by the network in response to the input representing an instance in a training data set is compared to the "correct" labeled output for that instance, an error signal representing the difference between the output and the labeled output is calculated, and the weights associated with the connections are adjusted to minimize that error as the error signal is backward propagated through the layers of the network. The network is considered "trained" when the errors for each of the outputs generated from the instances of the training data set are minimized.

The accuracy of a machine learning algorithm can be affected significantly by the quality of the data set used to train the algorithm. The training process can be computationally intensive and may require a significant amount of time on a conventional general-purpose processor. Accordingly, parallel processing hardware is used to train many types of machine learning algorithms. This is particularly useful for optimizing the training of neural networks, as the computations performed in adjusting the coefficients in neural networks lend themselves naturally to parallel implementations. Specifically, many machine learning algorithms and software applications have been adapted to make use of the parallel processing hardware within general-purpose graphics processing devices.

FIG. **2** is a generalized diagram of a machine learning software stack **200**. A machine learning application **202** can be configured to train a neural network using a training dataset or to use a trained deep neural network to implement machine intelligence. The machine learning application **202** can include training and inference functionality for a neural network and/or specialized software that can be used to train a neural network before deployment. The machine learning application **202** can implement any type of machine intelligence including but not limited to image recognition, mapping and localization, autonomous navigation, speech synthesis, medical imaging, or language translation.

Hardware acceleration for the machine learning application **202** can be enabled via a machine learning framework **204**. The machine learning framework **204** can provide a library of machine learning primitives. Machine learning primitives are basic operations that are commonly performed by machine learning algorithms. Without the machine learning framework **204**, developers of machine learning algorithms would have to create and optimize the main computational logic associated with the machine learning algorithm, then re-optimize the computational logic as new parallel processors are developed. Instead, the machine learning application can be configured to perform the computations using the primitives provided by the machine learning framework **204**. Example primitives include tensor convolutions, activation functions, and pooling, which are computational operations that are performed while training a convolutional neural network (CNN). The machine learning framework **204** can also provide primitives to implement basic linear algebra subprograms performed by many machine-learning algorithms, such as matrix and vector operations.

The machine learning framework **204** can process input data received from the machine learning application **202** and generate the appropriate input to a compute framework **206**. The compute framework **206** can abstract the underlying instructions provided to the GPGPU driver **208** to enable the machine learning framework **204** to take advantage of hardware acceleration via the GPGPU hardware **210** without requiring the machine learning framework **204** to have intimate knowledge of the architecture of the GPGPU hardware **210**. Additionally, the compute framework **206** can enable hardware acceleration for the machine learning framework **204** across a variety of types and generations of the GPGPU hardware **210**.

Machine Learning Neural Network Implementations

The computing architecture provided by embodiments described herein can be configured to perform the types of parallel processing that is particularly suited for training and deploying neural networks for machine learning. A neural network can be generalized as a network of functions having a graph relationship. As is known in the art, there are a variety of types of neural network implementations used in machine learning. One example type of neural network is the feedforward network, as previously described.

A second example type of neural network is the Convolutional Neural Network (CNN). A CNN is a specialized feedforward neural network for processing data having a known, grid-like topology, such as image data. Accordingly, CNNs are commonly used for compute vision and image recognition applications, but they also may be used for other types of pattern recognition such as speech and language processing. The nodes in the CNN input layer are organized into a set of "filters" (feature detectors inspired by the receptive fields found in the retina), and the output of each set of filters is propagated to nodes in successive layers of the network. The computations for a CNN include applying the convolution mathematical operation to each filter to produce the output of that filter. Convolution is a specialized kind of mathematical operation performed by two functions to produce a third function that is a modified version of one of the two original functions. In convolutional network terminology, the first function to the convolution can be referred to as the input, while the second function can be referred to as the convolution kernel. The output may be referred to as the feature map. For example, the input to a convolution layer can be a multidimensional array of data that defines the various color components of an input image. The convolution kernel can be a multidimensional array of parameters, where the parameters are adapted by the training process for the neural network.

Recurrent neural networks (RNNs) are a family of feedforward neural networks that include feedback connections between layers. RNNs enable modeling of sequential data by sharing parameter data across different parts of the neural network. The architecture for an RNN includes cycles. The cycles represent the influence of a present value of a variable on its own value at a future time, as at least a portion of the output data from the RNN is used as feedback for processing subsequent input in a sequence. This feature makes RNNs particularly useful for language processing due to the variable nature in which language data can be composed.

The figures described below present example feedforward, CNN, and RNN networks, as well as describe a general process for respectively training and deploying each of those types of networks. It can be understood that these descriptions are example and non-limiting as to any specific embodiment described herein and the concepts illustrated can be applied generally to deep neural networks and machine learning techniques in general.

The example neural networks described above can be used to perform deep learning. Deep learning is machine learning using deep neural networks. The deep neural networks used in deep learning are artificial neural networks composed of multiple hidden layers, as opposed to shallow neural networks that include a single hidden layer. Deeper neural networks are generally more computationally intensive to train. However, the additional hidden layers of the network enable multistep pattern recognition that results in reduced output error relative to shallow machine learning techniques.

Deep neural networks used in deep learning typically include a front-end network to perform feature recognition coupled to a back-end network which represents a mathematical model that can perform operations (e.g., object classification, speech recognition, etc.) based on the feature representation provided to the model. Deep learning enables machine learning to be performed without requiring hand crafted feature engineering to be performed for the model. Instead, deep neural networks can learn features based on statistical structure or correlation within the input data. The learned features can be provided to a mathematical model that can map detected features to an output. The mathematical model used by the network is generally specialized for the specific task to be performed, and different models can be used to perform different task.

Once the neural network is structured, a learning model can be applied to the network to train the network to perform specific tasks. The learning model describes how to adjust the weights within the model to reduce the output error of the network. Backpropagation of errors is a common method used to train neural networks. An input vector is presented to the network for processing. The output of the network is compared to the sought-after output using a loss function and an error value is calculated for each of the neurons in the output layer. The error values are then propagated backwards until each neuron has an associated error value which roughly represents its contribution to the original output. The network can then learn from those errors using an algorithm, such as the stochastic gradient descent algorithm, to update the weights of the of the neural network.

FIGS. **3A-3B** illustrate an example convolutional neural network. FIG. **3A** illustrates various layers within a CNN. As shown in FIG. **3A**, an example CNN used to model image processing can receive input **302** describing the red, green, and blue (RGB) components of an input image. The input **302** can be processed by multiple convolutional layers (e.g., first convolutional layer **304**, second convolutional layer **306**). The output from the multiple convolutional layers may optionally be processed by a set of fully connected layers **308**. Neurons in a fully connected layer have full connections to all activations in the previous layer, as previously described for a feedforward network. The output from the fully connected layers **308** can be used to generate an output result from the network. The activations within the fully connected layers **308** can be computed using matrix multiplication instead of convolution. Not all CNN implementations make use of fully connected layers **308**. For example, in some implementations the second convolutional layer **306** can generate output for the CNN.

The convolutional layers are sparsely connected, which differs from traditional neural network configuration found in the fully connected layers **308**. Traditional neural network layers are fully connected, such that every output unit interacts with every input unit. However, the convolutional layers are sparsely connected because the output of the convolution of a field is input (instead of the respective state value of each of the nodes in the field) to the nodes of the subsequent layer, as illustrated. The kernels associated with the convolutional layers perform convolution operations, the output of which is sent to the next layer. The dimensionality reduction performed within the convolutional layers is one aspect that enables the CNN to scale to process large images.

FIG. **3B** illustrates example computation stages within a convolutional layer of a CNN. Input to a convolutional layer **312** of a CNN can be processed in three stages of a convolutional layer **314**. The three stages can include a convolution stage **316**, a detector stage **318**, and a pooling stage **320**. The convolutional layer **314** can then output data to a successive convolutional layer. The final convolutional layer of the network can generate output feature map data or provide input to a fully connected layer, for example, to generate a classification value for the input to the CNN.

In the convolution stage **316** performs several convolutions in parallel to produce a set of linear activations. The convolution stage **316** can include an affine transformation, which is any transformation that can be specified as a linear transformation plus a translation. Affine transformations include rotations, translations, scaling, and combinations of these transformations. The convolution stage computes the output of functions (e.g., neurons) that are connected to specific regions in the input, which can be determined as the local region associated with the neuron. The neurons compute a dot product between the weights of the neurons and the region in the local input to which the neurons are connected. The output from the convolution stage **316** defines a set of linear activations that are processed by successive stages of the convolutional layer **314**.

The linear activations can be processed by a detector stage **318**. In the detector stage **318**, each linear activation is processed by a non-linear activation function. The non-linear activation function increases the nonlinear properties of the overall network without affecting the receptive fields of the convolution layer. Several types of non-linear activation functions may be used. One particular type is the rectified linear unit (ReLU), which uses an activation function defined as $f(x)=\max(0,x)$, such that the activation is thresholded at zero.

The pooling stage **320** uses a pooling function that replaces the output of the second convolutional layer **306** with a summary statistic of the nearby outputs. The pooling function can be used to introduce translation invariance into the neural network, such that small translations to the input do not change the pooled outputs. Invariance to local translation can be useful in scenarios where the presence of a feature in the input data is weighted more heavily than the precise location of the feature. Various types of pooling functions can be used during the pooling stage **320**, including max pooling, average pooling, and l2-norm pooling. Additionally, some CNN implementations do not include a pooling stage. Instead, such implementations substitute and additional convolution stage having an increased stride relative to previous convolution stages.

The output from the convolutional layer **314** can then be processed by the next layer **322**. The next layer **322** can be an additional convolutional layer or one of the fully connected layers **308**. For example, the first convolutional layer **304** of FIG. **3**A can output to the second convolutional layer **306**, while the second convolutional layer can output to a first layer of the fully connected layers **308**.

FIG. **4** illustrates an example recurrent neural network. In a recurrent neural network (RNN), the previous state of the network influences the output of the current state of the network. RNNs can be built in a variety of ways using a variety of functions. The use of RNNs generally revolves around using mathematical models to predict the future based on a prior sequence of inputs. For example, an RNN may be used to perform statistical language modeling to predict an upcoming word given a previous sequence of words. The illustrated RNN **400** can be described as having an input layer **402** that receives an input vector, hidden layers **404** to implement a recurrent function, a feedback mechanism **405** to enable a 'memory' of previous states, and an output layer **406** to output a result. The RNN **400** operates based on time-steps. The state of the RNN at a given time step is influenced based on the previous time step via the feedback mechanism **405**. For a given time step, the state of the hidden layers **404** is defined by the previous state and the input at the current time step. An initial input (x_1) at a first time step can be processed by the hidden layer **404**. A second input (x_2) can be processed by the hidden layer **404** using state information that is determined during the processing of the initial input (x_1). A given state can be computed as $s_t=f(Ux_t+Ws_{t-1})$, where U and W are parameter matrices. The function f is generally a nonlinearity, such as the hyperbolic tangent function (Tanh) or a variant of the rectifier function $f(x)=\max(0, x)$. However, the specific mathematical function used in the hidden layers **404** can vary depending on the specific implementation details of the RNN **400**.

In addition to the basic CNN and RNN networks described, variations on those networks may be enabled. One example RNN variant is the long short-term memory (LSTM) RNN. LSTM RNNs are capable of learning long-term dependencies that may be utilized for processing longer sequences of language. A variant on the CNN is a convolutional deep belief network, which has a structure similar to a CNN and is trained in a manner similar to a deep belief network. A deep belief network (DBN) is a generative neural network that is composed of multiple layers of stochastic (random) variables. DBNs can be trained layer-by-layer using greedy unsupervised learning. The learned weights of the DBN can then be used to provide pre-train neural networks by determining an optimized initial set of weights for the neural network.

FIG. **5** illustrates training and deployment of a deep neural network. Once a given network has been structured for a task the neural network is trained using a training dataset **502**. Various training frameworks have been developed to enable hardware acceleration of the training process. For example, the machine learning framework **204** of FIG. **2** may be configured as a training framework **504**. The training framework **504** can hook into an untrained neural network **506** and enable the untrained neural network to be trained using the parallel processing resources described herein to generate a trained neural network **508**. To start the training process the initial weights may be chosen randomly or by pre-training using a deep belief network. The training cycle then be performed in either a supervised or unsupervised manner.

Supervised learning is a learning method in which training is performed as a mediated operation, such as when the training dataset **502** includes input paired with the sought-after output for the input, or where the training dataset includes input having known output and the output of the neural network is manually graded. The network processes the inputs and compares the resulting outputs against a set of expected or sought-after outputs. Errors are then propagated back through the system. The training framework **504** can adjust to adjust the weights that control the untrained neural network **506**. The training framework **504** can provide tools to monitor how well the untrained neural network **506** is converging towards a model suitable to generating correct answers based on known input data. The training process occurs repeatedly as the weights of the network are adjusted to refine the output generated by the neural network. The training process can continue until the neural network reaches a statistically relevant accuracy associated with a trained neural network **508**. The trained neural network **508** can then be deployed to implement any number of machine learning operations to generate an inference result **514** based on input of new data **512**.

Unsupervised learning is a learning method in which the network attempts to train itself using unlabeled data. Thus, for unsupervised learning the training dataset **502** can include input data without any associated output data. The untrained neural network **506** can learn groupings within the unlabeled input and can determine how individual inputs are related to the overall dataset. Unsupervised training can be used to generate a self-organizing map, which is a type of trained neural network **508** capable of performing operations useful in reducing the dimensionality of data. Unsupervised training can also be used to perform anomaly detection, which allows the identification of data points in an input dataset that deviate from the normal patterns of the data.

Variations on supervised and unsupervised training may also be employed. Semi-supervised learning is a technique in which in the training dataset **502** includes a mix of labeled and unlabeled data of the same distribution. Incremental learning is a variant of supervised learning in which input data is continuously used to further train the model. Incremental learning enables the trained neural network **508** to adapt to the new data **512** without forgetting the knowledge instilled within the network during initial training.

Whether supervised or unsupervised, the training process for particularly deep neural networks may be too computationally intensive for a single compute node. Instead of using a single compute node, a distributed network of computational nodes can be used to accelerate the training process.

Example Machine Learning Applications

Machine learning can be applied to solve a variety of technological problems, including but not limited to computer vision, autonomous driving and navigation, speech recognition, and language processing. Computer vision has traditionally been an active research areas for machine learning applications. Applications of computer vision range from reproducing human visual abilities, such as recognizing faces, to creating new categories of visual abilities. For example, computer vision applications can be configured to recognize sound waves from the vibrations induced in objects visible in a video. Parallel processor accelerated machine learning enables computer vision applications to be trained using significantly larger training dataset than previously feasible and enables inferencing systems to be deployed using low power parallel processors.

Parallel processor accelerated machine learning has autonomous driving applications including lane and road sign recognition, obstacle avoidance, navigation, and driving control. Accelerated machine learning techniques can be used to train driving models based on datasets that define the appropriate responses to specific training input. The parallel processors described herein can enable rapid training of the increasingly complex neural networks used for autonomous driving solutions and enables the deployment of low power inferencing processors in a mobile platform suitable for integration into autonomous vehicles.

Parallel processor accelerated deep neural networks have enabled machine learning approaches to automatic speech recognition (ASR). ASR includes the creation of a function that computes the probable linguistic sequence given an input acoustic sequence. Accelerated machine learning using deep neural networks have enabled the replacement of the hidden Markov models (HMMs) and Gaussian mixture models (GMMs) previously used for ASR.

Parallel processor accelerated machine learning can also be used to accelerate natural language processing. Automatic learning procedures can make use of statistical inference algorithms to produce models that are robust to erroneous or unfamiliar input. Example natural language processor applications include automatic machine translation between human languages.

The parallel processing platforms used for machine learning can be divided into training platforms and deployment platforms. Training platforms are generally highly parallel and include optimizations to accelerate multi-GPU single node training and multi-node, multi-GPU training, while deployed machine learning (e.g., inferencing) platforms generally include lower power parallel processors suitable for use in products such as cameras, autonomous robots, and autonomous vehicles.

Authenticator-Integrated GAN for Secure Deepfake Generation

As discussed above, implementations of the disclosure provide for an authenticator-integrated GAN for secure deepfake generation. As previously discussed, neural networks can be leveraged to generate synthetic content in which a person in an existing image or video is replaced with someone else's likeness. Such synthetic content is often referred to as a "deepfake". The main machine learning methods used to create deepfakes are based on deep learning and involve training generative neural network architectures, such as GANs. As noted above, GANs are a class of ML frameworks where two neural networks (e.g., a "generative network" (or generator) and a "discriminative network" (or discriminator)) contest with each other in a game (in the form of a zero-sum game, where one agent's gain is another agent's loss). Given a training set, the GAN learns to generate new data with the same statistics as the training set. The core idea of a GAN is based on the "indirect" training through a discriminator, which itself is also being updated dynamically. This means that the generator is not trained to minimize the distance to a specific image, but rather to fool the discriminator.

As deep fakes become more popular, their use with malicious intent is endangering public trust mechanisms. On the other hand, generative modeling has been used for positive purposes in media, entertainment, and augmented reality (AR)/virtual reality (VR) domains for decades. The proliferation of deepfakes can obscure the creative and authentic uses of generative models. Traditional authentication approaches (such as watermarking) become obsolete in this new context due to the complex generation process. Thus, implementations of the disclosure provide for authentication as a part of the generation process of GANs by creating trackable content.

Conventional methods for deepfake detection rely on training a classifier on a large collection of datasets to determine the common attributes that statistically work "well" for a group of subjects for deepfake detection. However, a drawback to the conventional approaches for deepfake detection is that they did not allow for marking mark content as originating from a particular generator. Conventional methods do not provide for this type of authentication of origin verification for GAN-generated content and/or GAN-based approaches.

Implementations of the disclosure address these drawbacks by providing an authenticator-integrated GAN architecture for deepfake origin verification. As noted above, GANs consist of a generator and a discriminator structure where the generator attempts to trick the discriminator to believe the generated content is real, and the discriminator attempts to classify the real and generated content correctly. Implementations of the disclosure augment the conventional GAN architecture with a third component: the authenticator (implemented as an authenticator neural network). As such, in implementations of the disclosure, the combination of the generative neural network, the discriminator neural network, and the authenticator neural network in combination comprise a GAN. In implementations of the disclosure, the authenticator can digest real and fake data, similar to a discriminator, and also can digest a private code (also referred to herein as an authentication code). The authenticator seeks to embed the private code into the generated samples by contributing to the generator loss, and seeks to learn an internal embedding of the private code related to the distribution of the generated samples from the generator. The generator helps the authenticator, in contrast to tricking the discriminator. As a result, implementations of the disclosure provide an approach to authenticate the GAN-generated content as originating from a GAN generator.

FIG. **6** depicts a GAN system **600** providing an authenticator-integrated GAN for secure deepfake generation, in accordance with implementations of the disclosure. In one embodiment, GAN system **600** can include a generator neural network **610**, a discriminator neural network **620**, and an authenticator neural network **630**. In some embodiments, one or more of generator neural network **610**, a discriminator neural network **620**, and an authenticator neural network **630** may be implemented in the same computing device. In some embodiments, one or more of generator neural network **610**, a discriminator neural network **620**, and an authenticator neural network **630** are implemented in separate computing devices and are communicably coupled via a network (not shown). Generator neural network **610**, a discriminator neural network **620**, and an authenticator neural network **630** may be implemented using hardware circuitry, such as one or more of a CPU, a GPU, a hardware accelerator, and so on. In one embodiment, generator neural network **610**, a discriminator neural network **620**, and an authenticator neural network **630** may be implemented using computing system **100** described with respect to FIG. **1**. GAN system **600** may include more or less components than illustrated and described herein and is not limited to the particular example depiction of FIG. **6**.

More generally, the example GAN system **600** of FIG. **6** may be implemented by hardware, software, firmware and/or any combination of hardware, software and/or firmware. Thus, for example, any of the example generator neural network **610**, the example discriminator neural network **620**, and/or the example authenticator neural network **630** could be implemented by one or more analog or digital circuit(s), logic circuits, programmable processor(s), programmable controller(s), graphics processing unit(s) (GPU(s)), digital signal processor(s) (DSP(s)), application specific integrated circuit(s) (ASIC(s)), programmable logic device(s) (PLD(s)) and/or field programmable logic device(s) (FPLD(s)).

GAN system **600** may provide a machine learning framework including a generator neural network **610** (may be referred to herein as generator **610**), a discriminator neural network **620** (may be referred to herein as discriminator **620**), and an authenticator neural network **630** (may be referred to herein as authenticator **630**). In one embodiment, the generator neural network **610** is configured to learn to map from a latent space to a data distribution of interest. The discriminator neural network **620** is configured to distinguish candidates produced by the generator neural network **610** from a true data distribution. The generator neural network's **610** training objective is to increase the error rate of the discriminator neural network **620** (e.g., "fool" the discriminator **620** by producing novel candidates that the discriminator **620** thinks are not synthesized (are part of the true data distribution)).

A known data set, such as real data **650**, can serve as the initial training data for the discriminator neural network **620**. Training the discriminator neural network **620** involves presenting the discriminator **620** with one or more samples from the training set of real data **650** until the discriminator **620** achieves an acceptable accuracy. The generator **610** trains based on whether it succeeds in fooling the discriminator **620**. The generator **610** may be seeded with randomized input that is sampled from a predefined latent space (e.g., a multivariate normal distribution). Thereafter, candidates synthesized (i.e., generated output **640**) by the generator **610** are evaluated by the discriminator **620**. Independent backpropagation procedures can be applied to both networks of the generator **610** and discriminator **620** by contributing to a discriminator loss **622** and a generator loss **624**. The backpropagation procedures, using discriminator loss **622** and generator loss **624**, allow the generator **610** to produce (synthesize) improved samples of generated output **640**, while the discriminator **620** becomes more skilled at flagging the synthetic samples of generated output **640**. In one example, when the GAN system **600** is used for image generation, the generator neural network **610** may be a deconvolutional neural network, and the discriminator neural network **620** may be a convolutional neural network.

Implementations of the disclosure provide an approach for GAN system **600** to verify and authenticate the origin of GAN-generated content. In addition to the generator and a discriminator structure of the GAN system **600** (where the generator attempts to trick the discriminator to believe the generated content is real, and the discriminator attempts to classify the real and generated content correctly), implementations of the disclosure augment the conventional GAN architecture with an authenticator **630**. In one example, when the GAN system **600** is used for image generation, the authenticator neural network **630** may be a convolutional neural network.

In implementations of the disclosure, the authenticator neural network **630** can digest real and synthesized data, similar to the discriminator **620**. Furthermore, in implementations of the disclosure, the authenticator neural network **630** can digest an authentication code **670** (also referred to herein as a private code). In implementations of the disclosure, the authentication code **670** can be a sufficiently large string of characters, which can be the hash of a signal or a password. Instead of a hash, implementations can also add an encoder to create authentication codes **670** from given strings if the authentication code **670** should satisfy some predetermined specifications, coherent with the authenticator architecture.

The authenticator **630** seeks to embed the authentication code **670** into the generated output **640** of the generator **610** by contributing to a generator loss **634**. The authenticator **630** also seeks to learn an internal embedding of the authentication code **670** related to the distribution of the generated output **640** from the generator **610** by backpropagating an authenticator loss **632**. In implementations of the disclosure, the generator **610** helps the authenticator **630**, in contrast to tricking the discriminator **620**. As a result, implementations of the disclosure provide an approach to authenticate the GAN-generated content as originating from a GAN generator.

Implementations of the disclosure provide a variety of loss formulations including, but not limited to, an adversarial loss, an authenticator loss, and a reconstruction loss. The loss formulations are utilized as part of formulating an overall training objective of the GAN system **600**, including overall training objectives for the generator **610**, discriminator **620**, and authenticator **630** of GAN system **600**.

The adversarial loss is a loss function between the generator **610** and discriminator **620** that characterizes if the generated output **640** from generator **610** is following the distribution of the input samples from real data **650**. In some implementations, the adversarial loss (L_{adv}) between the generator (G) and the discriminator (D) on images (x) can be defined as follows:

$$L_{adv}=E_x[\log(D(x))]+E_x[\log(1-D(G(x)))],$$

where E_x is an expectation on x, D(x) is the output (e.g., probability value) of the discriminator **620** when image x is input to the discriminator **620**, and G(x) is the output (e.g., synthesized content) of the generator **610** when image x is input to the generator **610**.

The authenticator loss is a loss function with a target to maximize when a portion of the input to the authenticator **630** and the authentication code **670** for the authenticator **630** match (e.g., can recognize the authentication code in the generated output **640**), and to minimize when the input to the authenticator **630** does not come from the generator **610** (e.g., input to authenticator **630** is real data **650**). In one implementation, the authenticator loss (L_{aut}) on images (x) with authentication code (k) can be defined as follows:

$$L_{aut}=E_{x,k}[\log(A(G(x,k),k))+E_{x,k}[\log(1-A(x,k))],$$

where A(x) is the output (e.g., probability value) of the authenticator **630** when image x and the authentication code k **670** are input to the authenticator **630**.

The reconstruction loss is a loss function that reinforces the embedding of the authentication code **670** related to the distribution of the generated output **640** from the generator **610**. The reconstruction loss is utilized to reinforce the generator **610** creating images similar to the original image, even in the presence of the authentication code **670**. In one implementation, the reconstruction loss (L_{rec}) on images (x) with authentication code (k) can be defined as follows:

$$L_{rec}=E_{x,k}\|x-G(x,k)\|_2,$$

where E_x, k is the expectation on the tuple (x, k) and ||.||_2 is the l_2 norm that defines the pixel difference between the original image x and the generated image G(x, k).

Using the adversarial loss, the authenticator loss, and the reconstruction loss described above, the overall training objective for the generator **610**, discriminator **620**, and authenticator **630** in GAN system **600** can become:

$$\min_{G,A}\max_{D}(\lambda_A L_{adv}+\lambda_K L_{auth}+\lambda_R L_{rec}),$$

where the generator **610** and authenticator **630** seek to minimize the overall training objective and the discriminator **620** seeks to maximize the overall training objective, and where the values for the lambda parameter (λ), are hyperparameters to the GAN system **600** to balance the contribution of each loss item.

As a result, the generated output **640** of generator **610** contains an embedded authentication code **670**, which can be decoded as "passing" (e.g., verified) by the learned representation in the specific authenticator **630** that the generator **610** is trained with. To authenticate and/or verify content, the authenticator **630** and the authentication code **670** can be distributed for utilization in content confirmation by the authenticator **630**. As such, in implementations of the disclosure, the authenticator **630** can decode the content it has helped create (i.e., with the correct authentication code **670**), making its distribution secure.

For content creators, producers, artists, visual effects crew, etc., validation of the source and the authenticity of generated work is important. Implementations of the disclosure providing the authenticator-integrated GAN of GAN system **600** described with respect to FIG. **6** enable such validation and authentication of generated work. Implementations of the disclosure may also be utilized as integrated into editing software as a native way to authenticate synthesized (e.g., deepfake) content as those software instances begin to use GANs, such as GAN system **600**, for content creation.

FIG. **7** depicts a schematic of an illustrative flow **700** of an authenticator-integrated GAN system providing secure deepfake detection, in accordance with implementations of the disclosure. In some implementations, GAN system **600** described with respect to FIG. **6** may perform aspects of illustrative flow **700**. In one implementation, neural filters that are already being used in commercial software could employ the approach(es) of implementations of the disclosure for secure deepfake detection using an authenticator-integrated GAN.

For example, the flow **700** may be a content editing flow where an existing GAN-based neural filter (GAN filter **720**) is equipped with an authenticator-integrated GAN, such as GAN system **600** described with respect to FIG. **6**. In one implementation, flow **700** (e.g., content editing flow) may be performed by software that implements generation of deepfakes via a GAN filter **720**. The software may be an independent software vendor (ISV) capable of generating synthesized content. The flow begins with receiving input content **710**, applying a first set of filters (Filters A **715**) to the input content **710**, and then apply a transformation to the filtered content using GAN filter **720**.

The GAN filter **720** may be an authenticator-integrated GAN including a generator neural network (generator **722**), a discriminator neural network (discriminator **724**), an authenticator neural network (authenticator **726**), and a datastore **740**. The generator **722** may be the same as generator **610** described with respect to FIG. **6**, the discriminator **724** may be the same as discriminator **620** described with respect to FIG. **6**, and the authenticator **726** may be the same as authenticator **630** described with respect to FIG. **6**. In some implementations, additional filters (Filters B **730**) may be applied to the generated content from GAN filter **720** resulting in a final output **735** from the flow **700**.

In flow **700**, the authenticator code **725** is fed as input to the authenticator **726**. The authenticator code **725** may be hashed and stored in content metadata maintained in a change history datastore **750**. The filtered content that is output by the GAN filter **720** (and/or by Filters B **730**) may also contain an embedded representation of the authentication code **737**. At the end of the flow **700**, the synthetic content's embedded authentication code **737** can be fed to the authenticator **726**, or correlated with the metadata in change history datastore **750**, thereby creating a verifiable mechanism regarding the use of generative AI in the content.

FIG. **8** is a flow diagram illustrating an embodiment of a method **800** for a secure deepfake generation using an authenticator-integrated GAN. Method **800** may be performed by processing logic that may comprise hardware (e.g., circuitry, dedicated logic, programmable logic, etc.), software (such as instructions run on a processing device), or a combination thereof. More particularly, the method **800** may be implemented in one or more modules as a set of logic instructions stored in a machine- or computer-readable storage medium (also referred to herein as a non-transitory computer-readable storage medium) such as RAM, ROM, PROM, firmware, flash memory, etc., in configurable logic such as, for example, PLAs, FPGAs, CPLDs, in fixed-functionality logic hardware using circuit technology such as, for example, ASIC, CMOS or TTL technology, or any combination thereof.

The process of method **800** is illustrated in linear sequences for brevity and clarity in presentation; however, it is contemplated that any number of them can be performed in parallel, asynchronously, or in different orders. Further, for brevity, clarity, and ease of understanding, many of the components and processes described with respect to FIGS.

1-7 may not be repeated or discussed hereafter. In one implementation, GAN system **600** of FIG. **6**, may perform method **800**.

The example process of method **800** of FIG. **8** begins at block **810** where a processing device may generate, using a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network. In one implementation, the generative neural network can aim to trick the discriminator neural network to identify the generated samples as real content samples. At block **820**, the processing device may digest, using the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code.

Subsequently, at block **830**, the processing device may embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network by contributing to a generator loss provided to the generative neural network. Then, at block **840**, the processing device may generate, using the generative neural network, content comprising the embedded authentication code. Lastly, at block **850**, the processing device may verify, using the authenticator neural network, the content based on the embedded authentication code.

FIG. **9** is a flow diagram illustrating an embodiment of a method **900** for training an authenticator-integrated GAN for secure deepfake generation. Method **900** may be performed by processing logic that may comprise hardware (e.g., circuitry, dedicated logic, programmable logic, etc.), software (such as instructions run on a processing device), or a combination thereof. More particularly, the method **900** may be implemented in one or more modules as a set of logic instructions stored in a machine- or computer-readable storage medium such as RAM, ROM, PROM, firmware, flash memory, etc., in configurable logic such as, for example, PLAs, FPGAs, CPLDs, in fixed-functionality logic hardware using circuit technology such as, for example, ASIC, CMOS or TTL technology, or any combination thereof.

The process of method **900** is illustrated in linear sequences for brevity and clarity in presentation; however, it is contemplated that any number of them can be performed in parallel, asynchronously, or in different orders. Further, for brevity, clarity, and ease of understanding, many of the components and processes described with respect to FIGS. **1-8** may not be repeated or discussed hereafter. In one implementation, GAN system **600** of FIG. **6**, may perform method **900**.

The example process of method **900** of FIG. **9** begins at block **910** where a processing device may determine an adversarial loss between a generator and a discriminator of a GAN to differentiate between original content and generated content from the generator. Then, at block **920**, the processing device may determine an authenticator loss for an authenticator of the GAN to minimize when a portion of generated content from the generator and an authentication code for the authenticator match, and minimize when the generated content does not originate from the generator.

Subsequently, at block **930**, the processing device may determine a reconstruction loss to reinforce similarity of content in the presence of the authentication code of the authenticator. Lastly, at block **940**, the processing device may train the GAN to minimize for the generator and the authenticator and maximize for the discriminator a summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

FIG. **10** is a schematic diagram of an illustrative electronic computing device to enable an authenticator-integrated GAN for secure deepfake generation, according to some embodiments. In some embodiments, the computing device **1000** includes one or more processors **1010** including one or more processors cores **1018** and a model trainer **1064**, the model trainer **1064** to enable an authenticator-integrated GAN for secure deepfake generation, as provided in FIGS. **1-9**. In some embodiments, the computing device **1000** includes a hardware accelerator **1068**, the hardware accelerator including a machine learning model **1084**. In some embodiments, the computing device is to implement an authenticator-integrated GAN for secure deepfake generation implementing the machine learning model **1084** for efficient computer vision systems, as provided in FIGS. **1-9**.

The computing device **1000** may additionally include one or more of the following: cache **1062**, a graphical processing unit (GPU) **1012** (which may be the hardware accelerator in some implementations), a wireless input/output (I/O) interface **1020**, a wired I/O interface **1030**, memory circuitry **1040**, power management circuitry **1050**, non-transitory storage device **1060**, and a network interface **1070** for connection to a network **1072**. The following discussion provides a brief, general description of the components forming the illustrative computing device **1000**. Example, non-limiting computing devices **1000** may include a desktop computing device, blade server device, workstation, or similar device or system.

In embodiments, the processor cores **1018** are capable of executing machine-readable instruction sets **1014**, reading data and/or instruction sets **1014** from one or more storage devices **1060** and writing data to the one or more storage devices **1060**. Those skilled in the relevant art can appreciate that the illustrated embodiments as well as other embodiments may be practiced with other processor-based device configurations, including portable electronic or handheld electronic devices, for instance smartphones, portable computers, wearable computers, consumer electronics, personal computers ("PCs"), network PCs, minicomputers, server blades, mainframe computers, and the like. For example, machine-readable instruction sets **1014** may include instructions to implement an authenticator-integrated GAN for secure deepfake generation, as provided in FIGS. **1-9**.

The processor cores **1018** may include any number of hardwired or configurable circuits, some or all of which may include programmable and/or configurable combinations of electronic components, semiconductor devices, and/or logic elements that are disposed partially or wholly in a PC, server, or other computing system capable of executing processor-readable instructions.

The computing device **1000** includes a bus or similar communications link **1016** that communicably couples and facilitates the exchange of information and/or data between various system components including the processor cores **1018**, the cache **1062**, the graphics processor circuitry **1012**, one or more wireless I/O interfaces **1020**, one or more wired I/O interfaces **1030**, one or more storage devices **1060**, and/or one or more network interfaces **1070**. The computing device **1000** may be referred to in the singular herein, but this is not intended to limit the embodiments to a single computing device **1000**, since in some embodiments, there may be more than one computing device **1000** that incorporates, includes, or contains any number of communicably coupled, collocated, or remote networked circuits or devices.

The processor cores **1018** may include any number, type, or combination of currently available or future developed devices capable of executing machine-readable instruction sets.

The processor cores **1018** may include (or be coupled to) but are not limited to any current or future developed single- or multi-core processor or microprocessor, such as: on or more systems on a chip (SOCs); central processing units (CPUs); digital signal processors (DSPs); graphics processing units (GPUs); application-specific integrated circuits (ASICs), programmable logic units, field programmable gate arrays (FPGAs), and the like. Unless described otherwise, the construction and operation of the various blocks shown in FIG. **10** are of conventional design. Consequently, such blocks do not have to be described in further detail herein, as they can be understood by those skilled in the relevant art. The bus **1016** that interconnects at least some of the components of the computing device **1000** may employ any currently available or future developed serial or parallel bus structures or architectures.

The system memory **1040** may include read-only memory ("ROM") **1042** and random access memory ("RAM") **1046**. A portion of the ROM **1042** may be used to store or otherwise retain a basic input/output system ("BIOS") **1044**. The BIOS **1044** provides basic functionality to the computing device **1000**, for example by causing the processor cores **1018** to load and/or execute one or more machine-readable instruction sets **1014**. In embodiments, at least some of the one or more machine-readable instruction sets **1014** cause at least a portion of the processor cores **1018** to provide, create, produce, transition, and/or function as a dedicated, specific, and particular machine, for example a word processing machine, a digital image acquisition machine, a media playing machine, a gaming system, a communications device, a smartphone, or similar.

The computing device **1000** may include at least one wireless input/output (I/O) interface **1020**. The at least one wireless I/O interface **1020** may be communicably coupled to one or more physical output devices **1022** (tactile devices, video displays, audio output devices, hardcopy output devices, etc.). The at least one wireless I/O interface **1020** may communicably couple to one or more physical input devices **1024** (pointing devices, touchscreens, keyboards, tactile devices, etc.). The at least one wireless I/O interface **1020** may include any currently available or future developed wireless I/O interface. Example wireless I/O interfaces include, but are not limited to: BLUETOOTH®, near field communication (NFC), and similar.

The computing device **1000** may include one or more wired input/output (I/O) interfaces **1030**. The at least one wired I/O interface **1030** may be communicably coupled to one or more physical output devices **1022** (tactile devices, video displays, audio output devices, hardcopy output devices, etc.). The at least one wired I/O interface **1030** may be communicably coupled to one or more physical input devices **1024** (pointing devices, touchscreens, keyboards, tactile devices, etc.). The wired I/O interface **1030** may include any currently available or future developed I/O interface. Example wired I/O interfaces include, but are not limited to: universal serial bus (USB), IEEE 1394 ("FireWire"), and similar.

The computing device **1000** may include one or more communicably coupled, non-transitory, data storage devices **1060**. The data storage devices **1060** may include one or more hard disk drives (HDDs) and/or one or more solid-state storage devices (SSDs). The one or more data storage devices **1060** may include any current or future developed storage appliances, network storage devices, and/or systems. Non-limiting examples of such data storage devices **1060** may include, but are not limited to, any current or future developed non-transitory storage appliances or devices, such as one or more magnetic storage devices, one or more optical storage devices, one or more electro-resistive storage devices, one or more molecular storage devices, one or more quantum storage devices, or various combinations thereof. In some implementations, the one or more data storage devices **1060** may include one or more removable storage devices, such as one or more flash drives, flash memories, flash storage units, or similar appliances or devices capable of communicable coupling to and decoupling from the computing device **1000**.

The one or more data storage devices **1060** may include interfaces or controllers (not shown) communicatively coupling the respective storage device or system to the bus **1016**. The one or more data storage devices **1060** may store, retain, or otherwise contain machine-readable instruction sets, data structures, program modules, data stores, databases, logical structures, and/or other data useful to the processor cores **1018** and/or graphics processor circuitry **1012** and/or one or more applications executed on or by the processor cores **1018** and/or graphics processor circuitry **1012**. In some instances, one or more data storage devices **1060** may be communicably coupled to the processor cores **1018**, for example via the bus **1016** or via one or more wired communications interfaces **1030** (e.g., Universal Serial Bus or USB); one or more wireless communications interfaces **1020** (e.g., Bluetooth®, Near Field Communication or NFC); and/or one or more network interfaces **1070** (IEEE 802.3 or Ethernet, IEEE 802.10, or Wi-Fi®, etc.).

Processor-readable instruction sets **1014** and other programs, applications, logic sets, and/or modules may be stored in whole or in part in the system memory **1040**. Such instruction sets **1014** may be transferred, in whole or in part, from the one or more data storage devices **1060**. The instruction sets **1014** may be loaded, stored, or otherwise retained in system memory **1040**, in whole or in part, during execution by the processor cores **1018** and/or graphics processor circuitry **1012**.

The computing device **1000** may include power management circuitry **1050** that controls one or more operational aspects of the energy storage device **1052**. In embodiments, the energy storage device **1052** may include one or more primary (i.e., non-rechargeable) or secondary (i.e., rechargeable) batteries or similar energy storage devices. In embodiments, the energy storage device **1052** may include one or more supercapacitors or ultracapacitors. In embodiments, the power management circuitry **1050** may alter, adjust, or control the flow of energy from an external power source **1054** to the energy storage device **1052** and/or to the computing device **1000**. The power source **1054** may include, but is not limited to, a solar power system, a commercial electric grid, a portable generator, an external energy storage device, or any combination thereof.

For convenience, the processor cores **1018**, the graphics processor circuitry **1012**, the wireless I/O interface **1020**, the wired I/O interface **1030**, the storage device **1060**, and the network interface **1070** are illustrated as communicatively coupled to each other via the bus **1016**, thereby providing connectivity between the above-described components. In alternative embodiments, the above-described components may be communicatively coupled in a different manner than illustrated in FIG. **10**. For example, one or more of the above-described components may be directly coupled to other components, or may be coupled to each other, via one or more intermediary components (not shown). In another example, one or more of the above-described components may be integrated into the processor cores **1018** and/or the graphics processor circuitry **1012**. In some embodiments, all or a portion of the bus **1016** may be omitted and the components are coupled directly to each other using suitable wired or wireless connections.

Flowcharts representative of example hardware logic, machine readable instructions, hardware implemented state machines, and/or any combination thereof for implementing the system **100** of FIG. **1**, for example, are shown in FIGS. **8** and/or **9**. The machine readable instructions may be one or more executable programs or portion(s) of an executable program for execution by a computer processor such as the processor **1010** shown in the example computing device **1000** discussed above in connection with FIG. **10**. The program may be embodied in software stored on a non-transitory computer readable storage medium such as a CD-ROM, a floppy disk, a hard drive, a DVD, a Blu-ray disk, or a memory associated with the processor **1010**, but the program and/or parts thereof could alternatively be executed by a device other than the processor **1010** and/or embodied in firmware or dedicated hardware. Further, although the example program is described with reference to the flowcharts illustrated in FIGS. **8** and/or **9**, many other methods of implementing the example systems may alternatively be used. For example, the order of execution of the blocks may be changed, and/or some of the blocks described may be changed, eliminated, or combined. Additionally, or alternatively, any or all of the blocks may be implemented by one or more hardware circuits (e.g., discrete and/or integrated analog and/or digital circuitry, an FPGA, an ASIC, a comparator, an operational-amplifier (op-amp), a logic circuit, etc.) structured to perform the corresponding operation without executing software or firmware.

The machine readable instructions described herein may be stored in one or more of a compressed format, an encrypted format, a fragmented format, a compiled format, an executable format, a packaged format, etc. Machine readable instructions as described herein may be stored as data (e.g., portions of instructions, code, representations of code, etc.) that may be utilized to create, manufacture, and/or produce machine executable instructions. For example, the machine readable instructions may be fragmented and stored on one or more storage devices and/or computing devices (e.g., servers). The machine readable instructions may require one or more of installation, modification, adaptation, updating, combining, supplementing, configuring, decryption, decompression, unpacking, distribution, reassignment, compilation, etc. in order to make them directly readable, interpretable, and/or executable by a computing device and/or other machine. For example, the machine readable instructions may be stored in multiple parts, which are individually compressed, encrypted, and stored on separate computing devices, wherein the parts when decrypted, decompressed, and combined form a set of executable instructions that implement a program such as that described herein.

In another example, the machine readable instructions may be stored in a state in which they may be read by a computer, but require addition of a library (e.g., a dynamic link library (DLL)), a software development kit (SDK), an application programming interface (API), etc. in order to execute the instructions on a particular computing device or other device. In another example, the machine readable instructions may be configured (e.g., settings stored, data input, network addresses recorded, etc.) before the machine readable instructions and/or the corresponding program(s) can be executed in whole or in part. Thus, the disclosed machine readable instructions and/or corresponding program(s) are intended to encompass such machine readable instructions and/or program(s) regardless of the particular format or state of the machine readable instructions and/or program(s) when stored or otherwise at rest or in transit.

The machine readable instructions described herein can be represented by any past, present, or future instruction language, scripting language, programming language, etc. For example, the machine readable instructions may be represented using any of the following languages: C, C++, Java, C#, Perl, Python, JavaScript, HyperText Markup Language (HTML), Structured Query Language (SQL), Swift, etc.

As mentioned above, the example processes of FIGS. **8** and/or **9** may be implemented using executable instructions (e.g., computer and/or machine readable instructions) stored on (thereon) a non-transitory computer and/or machine readable medium such as a hard disk drive, a flash memory, a read-only memory, a compact disk, a digital versatile disk, a cache, a random-access memory and/or any other storage device or storage disk in which information is stored for any duration (e.g., for extended time periods, permanently, for brief instances, for temporarily buffering, and/or for caching of the information). As used herein, the term non-transitory computer readable medium is expressly defined to include any type of computer readable storage device and/or storage disk and to exclude propagating signals and to exclude transmission media.

"Including" and "comprising" (and all forms and tenses thereof) are used herein to be open ended terms. Thus, whenever a claim employs any form of "include" or "comprise" (e.g., comprises, includes, comprising, including, having, etc.) as a preamble or within a claim recitation of any kind, it is to be understood that additional elements, terms, etc. may be present without falling outside the scope of the corresponding claim or recitation. As used herein, when the phrase "at least" is used as the transition term in, for example, a preamble of a claim, it is open-ended in the same manner as the term "comprising" and "including" are open ended.

The term "and/or" when used, for example, in a form such as A, B, and/or C refers to any combination or subset of A, B, C such as (1) A alone, (2) B alone, (3) C alone, (4) A with B, (5) A with C, (6) B with C, and (7) A with B and with C. As used herein in the context of describing structures, components, items, objects and/or things, the phrase "at least one of A and B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. Similarly, as used herein in the context of describing structures, components, items, objects and/or things, the phrase "at least one of A or B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. As used herein in the context of describing the performance or execution of processes, instructions, actions, activities and/or steps, the phrase "at least one of A and B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B. Similarly, as used herein in the context of describing the performance or execution of processes, instructions, actions, activities and/or steps, the phrase "at least one of A or B" is intended to refer to implementations including any of (1) at least one A, (2) at least one B, and (3) at least one A and at least one B.

As used herein, singular references (e.g., "a", "an", "first", "second", etc.) do not exclude a plurality. The term "a" or "an" entity, as used herein, refers to one or more of that entity. The terms "a" (or "an"), "one or more", and "at least one" can be used interchangeably herein. Furthermore, although individually listed, a plurality of means, elements or method actions may be implemented by, e.g., a single unit or processor. Additionally, although individual features may be included in different examples or claims, these may possibly be combined, and the inclusion in different examples or claims does not imply that a combination of features is not feasible and/or advantageous.

Descriptors "first," "second," "third," etc. are used herein when identifying multiple elements or components which may be referred to separately. Unless otherwise specified or understood based on their context of use, such descriptors are not intended to impute any meaning of priority, physical order or arrangement in a list, or ordering in time but are merely used as labels for referring to multiple elements or components separately for ease of understanding the disclosed examples. In some examples, the descriptor "first" may be used to refer to an element in the detailed description, while the same element may be referred to in a claim with a different descriptor such as "second" or "third." In such instances, it should be understood that such descriptors are used merely for ease of referencing multiple elements or components.

The following examples pertain to further embodiments. Example 1 is an apparatus to facilitate implementation of an authenticator-integrated GAN for secure deepfake generation. The apparatus of Example 1 comprises one or more processors to: generate, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; digest, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network; generate, by the generative neural network, content comprising the embedded authentication code; and verify, by the authenticator neural network, the content based on the embedded authentication code.

In Example 2, the subject matter of Example 1 can optionally include wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN). In Example 3, the subject matter of any one of Examples 1-2 can optionally include wherein the authentication code comprises at least one of a hash of a signal or a password to create a string of characters. In Example 4, the subject matter of any one of Examples 1-3 can optionally include wherein the authentication code comprises an encoder to create authentication codes from given strings.

In Example 5, the subject matter of any one of Examples 1-4 can optionally include wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a distribution of original content input to the generative neural network. In Example 6, the subject matter of any one of Examples 1-5 can optionally include wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

In Example 7, the subject matter of any one of Examples 1-6 can optionally include wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to the distribution of the content from the generative neural network. In Example 8, the subject matter of any one of Examples 1-7 can optionally include wherein the generative neural network to train using an overall training objective comprising: minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

In Example 9, the subject matter of any one of Examples 1-8 can optionally include wherein the embedded authentication code is decoded and verified as authentic using a learned representation in the authenticator neural network, and wherein to authenticate the content, the authenticator neural network to decode the content created using the authentication code.

Example 10 is a non-transitory computer-readable storage medium for facilitating an authenticator-integrated GAN for secure deepfake generation. The non-transitory computer-readable storage medium of Example 10 having stored thereon executable computer program instructions that, when executed by one or more processors, cause the one or more processors to perform operations comprising: generating, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; digesting, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; embedding, by the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network; generating, by the generative neural network, content comprising the embedded authentication code; and verifying, by the authenticator neural network, the content based on the embedded authentication code; wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

In Example 11, the subject matter of Example 10 can optionally include wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a distribution of original content input to the generative neural network. In Example 12, the subject matter of Examples 10-11 can optionally include wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

In Example 13, the subject matter of Examples 10-12 can optionally include wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to the distribution of the content from the generative neural network. In Example 14, the subject matter of Examples 10-13 can optionally include wherein the generative neural network to train using an overall training objective comprising: minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

In Example 15, the subject matter of Examples 10-14 can optionally include wherein the embedded authentication code is decoded and verified as authentic using a learned representation in the authenticator neural network, and wherein to authenticate the content, the authenticator neural network decodes the content created using the authentication code.

Example 16 is a method for facilitating an authenticator-integrated GAN for secure deepfake generation. The method of Example 16 can include generating, by a processor using a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; digesting, by the processor using the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; embedding, by the processor using the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network; generating, by the processor using the generative neural network, content comprising the embedded authentication code; and verifying, by the processor using the authenticator neural network, the content based on the embedded authentication code; wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

In Example 17, the subject matter of Example 16 can optionally include wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a distribution of original content input to the generative neural network. In Example 18, the subject matter of any one of Examples 16-17 can optionally include wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

In Example 19, the subject matter of any one of Examples 16-18 can optionally include wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to the distribution of the content from the generative neural network. In Example 20, the subject matter of any one of Examples 16-19 can optionally include wherein the generative neural network to train using an overall training objective comprising: minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

Example 21 is a system for facilitating an authenticator-integrated GAN for secure deepfake generation. The system of Example 21 can optionally include a memory, and a processor communicably coupled to the memory. The processor of the system of Example 21 can generate, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; digest, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network; generate, by the generative neural network, content comprising the embedded authentication code; and verify, by the authenticator neural network, the content based on the embedded authentication code.

In Example 22, the subject matter of Example 21 can optionally include wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN). In Example 23, the subject matter of any one of Examples 21-22 can optionally include wherein the authentication code comprises at least one of a hash of a signal or a password to create a string of characters. In Example 24, the subject matter of any one of Examples 21-23 can optionally include wherein the authentication code comprises an encoder to create authentication codes from given strings.

In Example 25, the subject matter of any one of Examples 21-24 can optionally include wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a distribution of original content input to the generative neural network. In Example 26, the subject matter of any one of Examples 21-25 can optionally include wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

In Example 27, the subject matter of any one of Examples 21-26 can optionally include wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to the distribution of the content from the generative neural network. In Example 28, the subject matter of any one of Examples 21-27 can optionally include wherein the generative neural network to train using an overall training objective comprising: minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

In Example 29, the subject matter of any one of Examples 21-28 can optionally include wherein the embedded authentication code is decoded and verified as authentic using a learned representation in the authenticator neural network, and wherein to authenticate the content, the authenticator neural network to decode the content created using the authentication code.

Example 30 is an apparatus for facilitating an authenticator-integrated GAN for secure deepfake generation according to implementations of the disclosure. The apparatus of Example 30 can comprise means for generating, using a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network aiming to trick the discriminator neural network to identify the generated samples as real content samples; means for digesting, using the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code; means for embedding, using the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network; means for generating, using the generative neural network, content comprising the embedded authentication code; and means for verifying, using the authenticator neural network, the content based on the embedded authentication code; wherein the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

In Example 31, the subject matter of Example 30 can optionally include the apparatus further configured to perform the method of any one of the Examples 17 to 20.

Example 32 is at least one machine readable medium comprising a plurality of instructions that in response to being executed on a computing device, cause the computing device to carry out a method according to any one of Examples 16-20. Example 33 is an apparatus for facilitating an authenticator-integrated GAN for secure deepfake generation, configured to perform the method of any one of Examples 16-20. Example 34 is an apparatus for facilitating an authenticator-integrated GAN for secure deepfake generation comprising means for performing the method of any one of claims **16** to **20**. Specifics in the Examples may be used anywhere in one or more embodiments.

The foregoing description and drawings are to be regarded in an illustrative rather than a restrictive sense. Persons skilled in the art can understand that various modifications and changes may be made to the embodiments described herein without departing from the broader spirit and scope of the features set forth in the appended claims.

What is claimed is:

1. An apparatus comprising:

one or more processors to:

generate, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network is to trick the discriminator neural network to identify the generated samples as real content samples;

digest, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code;

embed, by the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network;

generate, by the generative neural network, content comprising the embedded authentication code; and

verify, by the authenticator neural network, the content based on the embedded authentication code.

2. The apparatus of claim **1**, wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

3. The apparatus of claim **1**, wherein the authentication code comprises at least one of a hash of a signal or a password to create a string of characters.

4. The apparatus of claim **1**, wherein the authentication code comprises an encoder to create authentication codes from given strings.

5. The apparatus of claim **1**, wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a first distribution of original content input to the generative neural network.

6. The apparatus of claim **5**, wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

7. The apparatus of claim **6**, wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to a second distribution of the content from the generative neural network.

8. The apparatus of claim **7**, wherein the generative neural network to train using an overall training objective comprising:

minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and

maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

9. The apparatus of claim **1**, wherein the embedded authentication code is decoded and verified as authentic using a learned representation in the authenticator neural network, and wherein to authenticate the content, the authenticator neural network to decode the content created using the authentication code.

10. A non-transitory computer-readable storage medium having stored thereon executable computer program instructions that, when executed by one or more processors, cause the one or more processors to perform operations comprising:

generating, by a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network is to trick the discriminator neural network to identify the generated samples as real content samples;

digesting, by the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code;

embedding, by the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network;

generating, by the generative neural network, content comprising the embedded authentication code; and

verifying, by the authenticator neural network, the content based on the embedded authentication code;

wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

11. The non-transitory computer-readable storage medium of claim **10**, wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a first distribution of original content input to the generative neural network.

12. The non-transitory computer-readable storage medium of claim **11**, wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

13. The non-transitory computer-readable storage medium of claim **12**, wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to a second distribution of the content from the generative neural network.

14. The non-transitory computer-readable storage medium of claim **13**, wherein the generative neural network to train using an overall training objective comprising:

minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and

maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

15. The non-transitory computer-readable storage medium of claim **10**, wherein the embedded authentication code is decoded and verified as authentic using a learned representation in the authenticator neural network, and wherein to authenticate the content, the authenticator neural network decodes the content created using the authentication code.

16. A method comprising:

generating, by a processor using a generative neural network, samples based on feedback received from a discriminator neural network and from an authenticator neural network, the generative neural network is to trick the discriminator neural network to identify the generated samples as real content samples;

digesting, by the processor using the authenticator neural network, the real content samples, the generated samples from the generative neural network, and an authentication code;

embedding, by the processor using the authenticator neural network, the authentication code into the generated samples from the generative neural network as an embedded authentication code by contributing to a generator loss provided to the generative neural network;

generating, by the processor using the generative neural network, content comprising the embedded authentication code; and

verifying, by the processor using the authenticator neural network, the content based on the embedded authentication code;

wherein a combination of the generative neural network, the discriminator neural network, and the authenticator neural network comprise a generative adversarial network (GAN).

17. The method of claim **16**, wherein the generative neural network to generate adversarial loss comprising a first loss function between the generative neural network and the discriminator neural network, and wherein the first loss function is to characterize whether the content from the generative neural network is following a first distribution of original content that is input to the generative neural network.

18. The method of claim **17**, wherein the generative neural network to generate authenticator loss comprising a second loss function having a target to maximize when a match occurs between a portion of input to the authenticator neural network and the authentication code for the authenticator neural network, and to minimize when the input to the authenticator neural network does not originate from the generative neural network.

19. The method of claim **18**, wherein the generative neural network to generate reconstruction loss comprising a third loss function to reinforce embedding of the authentication code related to a second distribution of the content from the generative neural network.

20. The method of claim **19**, wherein the generative neural network to train using an overall training objective comprising:

minimizing, for the generative neural network and the authenticator neural network, a summation of the adversarial loss, the authenticator loss, and the reconstruction loss; and

maximizing, for the discriminator neural network, the summation of the adversarial loss, the authenticator loss, and the reconstruction loss.

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